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EVALUATION OF SOCIAL PREFERENCES FOR WOODY BIOMASS ENERGY IN THE US MOUNTAIN WEST

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Evaluation of Social Preferences for Woody Biomass Energy in the US Mountain West

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There are substantial opportunities for mechanized thinning treatments to reduce the likelihood of severe and damaging wildfires and improve forest health in the public forests of the Western US. These treatments could also produce woody biomass that can be used to generate renewable energy and displace fossil fuels. Although woody biomass energy is often not financially competitive with fossil fuels, financial analysis alone is an incomplete method of comparison because of the significant negative environmental externalities imposed by the burning of fossil fuels, and potential positive externalities associated with woody biomass energy generation. It is possible that when non-market costs and benefits are accounted for, the economic efficiency of woody biomass energy will compare more favorably to fossil fuels.

This study employed the choice modeling method in Arizona, Colorado, and Montana, to examine marginal willingness to pay (MWTP) for woody biomass energy produced from treatments in public forests. Positive and statistically significant MWTP is found for woody biomass energy generation, improving forest health, reducing risk of large wildfires, and improving air quality. Results from a latent class model reveal that sociodemographic and attitudinal characteristics are significant determinants of preferences about public forestland management for woody biomass energy generation. Four distinct classes of respondents were identified. These findings can be used by policy makers and public land managers to estimate the social benefits of utilizing residues from public forest restoration or fuel treatment programs to generate energy.

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Introduction

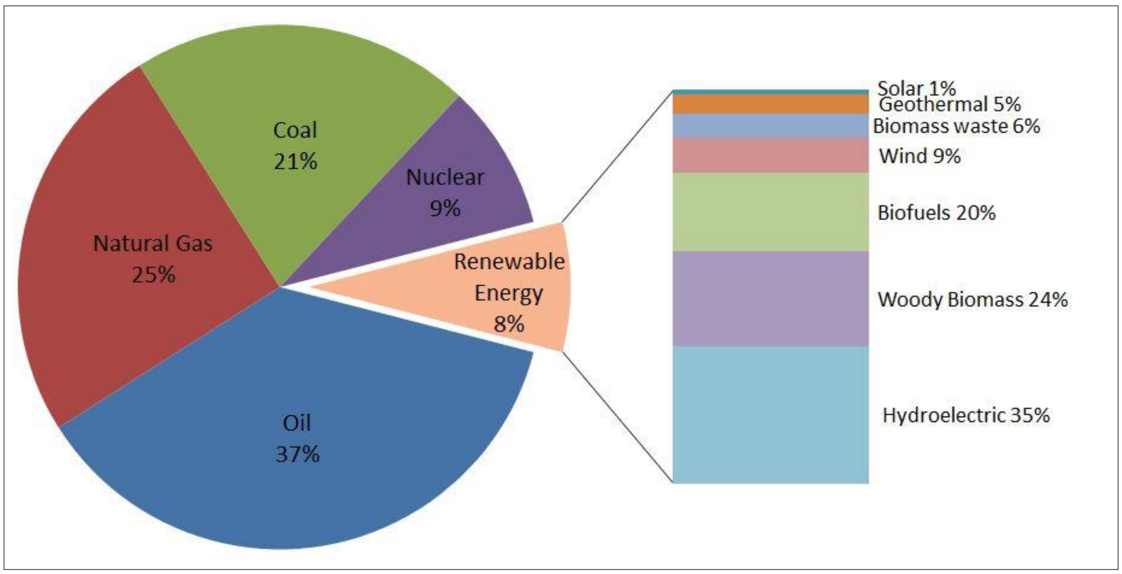
1.1 Climate Change and the Need for Renewable Energy

Climate change is one of the most pressing issues facing the world today. Impacts such as rising sea levels, increased severe weather events and declining agricultural yields could result in economic costs ranging from 5% to 20% of global annual GDP (Stern 2007). There is consensus amongst scientists that the major cause is anthropogenic greenhouse gas emissions, mainly from the consumption of fossil fuels (Edenhofer et al. 2012). One key action for mitigating the impacts of climate change is to replace a portion of fossil fuel energy generation with energy from renewable sources (Edenhofer et al. 2012).

In the United States, federal legislation has been passed to address climate change through mandating reductions in carbon dioxide emissions from fossil fuel energy generation (EPA 2015), and encouraging increased renewable energy generation from solar, wind, hydroelectric, geothermal and biomass (United States Congress 2005, United States Congress 2007). At the state level, 30 states in the US have adopted renewable energy portfolio standards or goals, encouraging or mandating increases in renewable energy generation (EIA 2012).

Despite these efforts, only 8% of energy consumption in the US was generated using renewable sources in 2011 (Figure 1.1). The largest portion of renewable energy consumption (35%) was supplied by hydroelectric power (EIA 2015). It may come as a surprise to some that the second largest portion of renewable energy consumption, ahead of wind and solar, was produced from wood. Wood and wood waste from logging and milling operations supplied 24% of all renewable energy, and just over 2% of total energy consumption in 2011 (EIA 2015). The potential for substantial increases in the amount of energy produced with wood exists, with one study finding that woody biomass has the potential to supply up to 10% of US energy needs (Zerbe 2006). Woody biomass is defined by the US Forest Service of the US Department of Agriculture and other federal agencies as the by-products of forest management such as limbs, tops, needs, leaves and other woody parts of trees and woody plants that are grown in a forest, woodland, or rangeland environment (USDA 2003). In this context, woody biomass utilization includes the harvest and use of these materials to produce bioenergy and energy feedstocks (USDA 2003).

Figure 1.1 US Energy Consumption by Source, 2011



Source: US EIA (2015)

Given the potential for woody biomass energy, one might ask why more energy is not currently produced this way. One explanation is that the high production costs of woody biomass energy relative to fossil fuels creates a barrier to expansion (Gan and Smith 2006). Indeed, the growth of renewable energy technologies is often limited because they struggle to compete financially with fossil fuels (Edenhofer et al. 2012). However, because of the significant negative environmental externalities imposed by the burning of fossil fuels, and the potential positive externalities associated with renewable energy generation, financial analysis alone provides an incomplete method of comparison. In order to compare the relative socioeconomic efficiency of alternative energy generation strategies, the positive and negative externalities from fossil fuels and alternative energy sources need to be valued and included in the decision making process. It is possible that when the non-market costs and benefits are accounted for, the economic efficiency of woody biomass energy will compare more favorably to fossil fuels.

The potential external effects associated with woody biomass energy arise mainly as a result of changes in the condition of forests. In the Western US, millions of acres of forest are departed from their historic conditions due to decades of wildfire suppression, livestock grazing, and poor timber harvesting practices (Wienk et al. 2004, Hutto 2008). These overgrown and structurally homogenous forests are less resilient to natural and manmade disturbances, less able to support a variety of native plant and animal communities (Huntzinger 2003, Hiers et al. 2007), and are more likely to experience unusually severe and damaging wildfires (Schwilk et al. 2009), that can threaten numerous human and ecological values (Graham et al. 2004).

Although wildfires are a natural and essential part of forest ecosystems, they have become larger and more frequent as a result of climate change and past management decisions (Gorte 2013). They can have substantial economic costs when they damage human assets like homes and watersheds, or blanket large areas with smoke that reduces air quality. The combination of larger and more frequent wildfires, and increased development in the wildland-urban interface resulted in a tripling of federal expenditures on wildfire suppression from $1 billion to $3 billion between 1990 and 2002, accounting for over half of the US Forest Service's annual budget (Gorte 2013).

These forest conditions can be mitigated using mechanized thinning treatments, prescribed wildland fire, or a combination of the two (Rummer et al. 2005). Mechanized thinning treatments can reduce the likelihood and severity of large wildfires by using heaving equipment to remove ladder fuels, like small trees and shrubs, that allow surface fires to climb into the forest canopy (Graham et al. 2004, Stephens et al. 2009). Mechanized thinning produces significant amounts of small diameter trees, tree tops, and limbs that are typically piled and burned on site for disposal (Jones et al. 2010). Alternatively, a potential market for residues is as feedstock for woody biomass energy generation facilities. Mechanized thinning treatments can be expensive to implement, with average treatment costs of $200 per acre (Rummer et al. 2005). With the budgets of public land management agencies often negatively impacted by fire suppression activities, cost can be a limiting factor in the amount of acres treated. By creating a potentially profitable use for forest residues, the utilization of woody biomass for energy production may facilitate more acres of restoration treatments. Treatment of public forests in the Western US provides a large potential source of woody biomass feedstock for energy generation, with over 28 million acres of severely departed timberland containing upwards of 570 million dry tons of biomass that could be removed by mechanized thinning treatments (Rummer et al. 2005).

The effects associated with utilizing woody biomass for energy generation are not captured in markets. Therefore, in order to determine if utilizing this source of biomass can be a socioeconomically efficient method for energy production, public preferences toward the potential environmental outcomes must be quantified. This information can reveal how much the public is willing to pay for energy generated this way, which potential benefits are most highly valued and what potential tradeoffs they are willing to make. This research will facilitate socioeconomic evaluation of woody biomass energy by quantifying the nonmarket economic effects associated with its use.

1.2 Goals and Objectives

The goal of this research is to support socioeconomically efficient decision making in forest management and renewable energy policy in the Mountain West of the United States. In order to assess the socioeconomic efficiency of any management action that would increase the amount of woody biomass harvested from public forests, public preferences toward the potential outcomes need to be quantified. By contributing values for nonmarket costs and benefits to the literature, the research will aid in the comparison of woody biomass with other energy options, as well as evaluation of specific renewable energy and forest management policies. The research also aims to contribute to the advancement of survey methods for the valuation of natural resources by building our understanding of cost effectiveness of conducting nonmarket valuation surveys. In order to achieve these goals, multiple research objectives were pursued. They are:

1) To quantify willingness of residents of the Mountain West to pay for energy generated with woody biomass from public forestland.

2) To quantify the tradeoffs that Mountain West residents are willing to make between woody biomass energy generation and other public forest land management objectives that can be affected by changes in woody biomass energy generation.

3) To determine in what ways sociodemographic and attitudinal characteristics determine preferences toward woody biomass energy and associated environmental effects, and whether preferences vary systematically between subpopulations hypothesized to have distinct preferences. Subpopulations of interest include, a) people who reside in non-attainment airsheds and those who don't, b) people who reside in forested areas versus those in non-forested areas, c) urban residents versus rural residents.

4) To compare the relative efficiency of multiple survey distribution modes.

1.3 Contribution to the literature

Few studies to date have attempted to value externalities associated with woody biomass energy generation. This research contributes to the literature on the economic evaluation of woody biomass energy by evaluating social preferences in the Mountain West of the United States. While studies have been conducted in Spain (Solino et al. 2012), and the US South (Susaeta et al. 2011), no past studies have evaluated social preferences regarding woody biomass energy in the Western United States, nor have previous studies evaluated preferences specifically toward feedstock generated by forest restoration treatments on public forests. The Western US has unique geographic, ecological, and socioeconomic characteristics that affect the management and utilization of natural resources - perhaps the most significant of which in this context is the high proportion of public lands compared to other parts of the country. Compared to the landscapes of the eastern and southern United States, which are dominated by private ownership, public preferences are more relevant to, and can be more readily accommodated within, forest management and policy in the western US. This research also contributes to the literature on nonmarket valuation survey methodology by being the first to compare the cost effectiveness of mail and internet-based survey modes for a choice modeling survey. Only one nonmarket valuation survey has compared the cost effectiveness of an internet-based survey to other survey modes, and it was with respect to a travel cost study (Fleming and Bowden 2009).

1.4Organization of the Dissertation

The dissertation continues in chapter 2 with a framing of the questions surrounding woody biomass energy, including comparison with other renewable sources of energy, exploration of the current and potential future role for woody biomass energy, and an overview of the opportunities and challenges for the technology in the United States. Chapter 2 also contains a review of the nonmarket costs and benefits of utilizing woody biomass for energy generation. In chapter 3, the economic methods used in the research are described. This includes a description of the conceptual framework upon which nonmarket valuation is built, an overview of the multiple methods that exist in the nonmarket valuation toolbox, a detailed description of the choice experiment method, and the derivation of economic welfare measures from choice experiment data. Case study methods are described separately in chapter 4. This includes an overview of the study area, the development of the choice experiment survey, and the data collection process. Chapters 5, 6, and 7 are self-contained manuscripts, formatted for submission to peer-reviewed academic journals. Chapter 5 quantifies willingness to pay for an increase in woody biomass energy in Montana. Chapter 6 analyzes social preferences toward woody biomass energy generation in Arizona, Colorado, and Arizona, with a focus on the attitudinal and sociodemographic characteristics that determine people's preferences. In Chapter 7, three different survey modes for collecting choice experiment data collection are compared based on cost-effectiveness, magnitude of welfare measures elicited from respondents, and ability to collect a representative sample of the population. Finally, in chapter 8, implications of the key findings from the three manuscripts are discussed and conclusions are drawn.

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Chapter 2

Overview of Woody Biomass Energy

As identified in the introduction, the goal of this research is to support socioeconomically efficient decision making in forest management and renewable energy policy by quantifying nonmarket economic effects of utilizing woody biomass from public forests to produce energy. Without a proper frame of reference for this research, it is not possible to make meaningful interpretations of the results. Chapter 2 provides background information that establishes the context for where woody biomass lies in the broader landscape of renewable energy generation. The chapter begins by reviewing woody biomass and other renewable energy sources based on their performance across several common metrics[1]. Then, in the section 2, the potential role for woody biomass in the US energy portfolio is discussed and opportunities and challenges are identified. Finally, in section 3, the non-market environmental effects associated with woody biomass harvest and energy generation are discussed.

2.1 Comparison of Alternative Sources of Renewable Energy

Woody biomass energy is one of multiple options that the United States has for expanding its renewable energy portfolio. As seen in figure 1.1, the largest current sources of renewable energy generation in the US are hydroelectric, wood, biofuels, wind, biomass waste, geothermal, and solar (EIA 2010). Each type of energy generation has some characteristics that make it more desirable than others and some characteristics for which it is less desirable. Each of these characteristics can be quantified

[1] In some cases, metrics of comparison are not available for woody biomass specifically. Therefore in some cases, more general classifications such as biomass energy, biopower, and bioenergy are used. Although implications likely vary between the sub-classifications of energy produced with biomass, they can still provide context for how woody biomass energy compares to other renewable energy options. Unless otherwise specified, biomass energy is electricity that is generated using a wide variety of biomass feedstocks, which can include: agricultural crops and residues, forest residues, municipal wood waste, animal manure, and gases from municipal and agricultural waste. Biopower refers to energy produced from the same wide variety of biomass feedstocks and can include both electric and thermal energy. These estimates do not include liquid biofuels like ethanol.

using metrics that allow for comparison with other energy sources. This section evaluates woody biomass energy and other renewable energy options according to:

- potential future production;
- financial cost of production;
- potential to supply peak-load energy demands;
- life cycle assessment; and
- non-market costs and benefits.

2.1.1 Potential Future Production

The quantity of energy that will be supplied using each renewable source in the future depends on technical, economic, market, and social factors. Estimates of the potential future production of woody biomass energy are highly dependent on the physical amount of available for energy production, which depends on economic factors like supply and demand in markets for competing woody biomass uses, and logistics costs, which include harvest, processing, transportation and storage. Although estimates are highly variable, they consistently suggest that the potential exists to generate a significant amount of energy with woody biomass. Perlack and Stokes (2011) put the total annual resource potential of biomass at 1,366 million dry tons (368 million dry tons from forest resources and 998 million dry tons from agriculture). Gan and Smith (2006) assessed the potential supply of forest biomass from logging residues like limbs, tops and small non-commercial trees, in the US to be 13.9 million dry tons, which could be used to generate 26 terawatt-hours (TWh) of electricity annually. Sedjo (1997) found that woody biomass could supply 0.05 TWh of electrical capacity in the US. It has also been estimated that woody biomass could eventually supply up to 10% of US energy consumption (Zerbe 2006).

The rest of this section focuses on only the technical potential of different renewable energy sources. Technical potential represents the upper-bounds estimate of the achievable energy generation of a given energy technology based solely on the physical availability of the resource without considering the effects of other factors like production costs and relevant policies.

Table 2.1 presents results from a spatial analysis by Lopez et al. (2012) that estimated the technical potential of different renewable energy technologies in the US, based on: physical measures of resource availability, system performance, topographic limitations, and environmental and land-use constraints. According to the analysis, solar photovoltaic (solar PV) has by far the largest technical potential of any renewable energy type with 282,800 TWh. Onshore wind energy comes in a distant second with 32,700 TWh, followed closely by geothermal with 31,600 TWh. Biopower and hydropower come in fourth and fifth on the list with respective technical potential of 500 TWh and 300 TWh, significantly lower than the other renewable energy types. These results stand in stark contrast to the current levels of renewable electricity generation, with hydropower providing the largest amount, followed by wind, biopower, geothermal, and solar in a distance fifth place (Table 2.2). To put the estimates in perspective, in 2013 net electricity generation in the US was 4,096 TWh, significantly less than the technical potential of solar PV energy, onshore wind power, and geothermal power.

Hydropower is a mature and heavily developed energy source in the US. The fact that it provides the largest share of renewable energy currently, and has the lowest technical potential suggests that it has less room for growth in the future than other renewable energy sources. Fifty three percent of the technical capacity of hydropower in North America has been developed and although that still leaves many technically feasible sites for hydropower installations many of the most economically feasible hydropower sites have already been developed (Kumar et al. 2011).

Globally, solar energy is the most abundant of all renewable energy sources, with the earth intercepting a practically inexhaustible amount of solar energy (Arvizu et al. 2011). In fact, the estimated technical potential for solar PV energy in the US far outweighs even the current total global electricity generation amount of 21,532 TWh (EIA 2015a). The fact that in the US, solar currently provides the smallest amount of energy generation of commonly considered renewable sources means that it has the largest technical potential for increased levels of energy generation. Although less than solar, the difference between the technical potential of wind power and its current level of production suggest that it has significant room for expanded production as well. The technical room for growth of geothermal energy is similar to wind power.

According to the analysis by Lopez et al. (2012), which was based on county-level estimates of solid biomass feedstocks from agricultural crop residues, forest residues, primary and secondary mill residues, and urban wood waste, as well as methane emissions from animal manure, wastewater treatment plants and landfills, and an assumption of 1.1 megawatt-hours (MWh) of electricity per bone-dry ton of biomass; the technical potential of biopower is significantly lower than solar, wind and geothermal energy generation.

Table 2.1. Estimated Technical Potential for United States

Rank	Energy Type	Generation Potential (TWh)
1.	Utility- Scale Solar PV	282,800
2.	Wind Onshore	32,700
3.	Geothermal	31,600
4.	Biopower	500
5.	Hydropower	300

Source Lopez et al. (2012)

Table 2.2 Net Electricity Generation, 2013

Rank	Energy Type	Net Generation (TWh)
1.	Hydropower	268.6
2.	Wind	167.8
3.	Biopower	60.9
4.	Geothermal	15.8
5.	Solar PV and Solar Thermal	9.0

Source: http://www.eia.gov/electricity/annual/html/epa_01_02.html

2.1.1.1 Regional Variation in Technical Potential

The efficiency of conversion and technical feasibility of different renewable energy sources varies regionally because of geographic, topographic and climatic characteristics that determine what resources are most plentiful. As a result, the nation-wide rankings of technical potential do not hold for every state of region across the country. Hydropower is produced by the energy of water moving from higher elevations to lower elevations. Therefore, the technical potential of hydropower depends both on the presence of rivers and on the terrain gradient through which they flow. As a result, regions with significant topographic relief and high amounts of precipitation have the most technical potential for hydropower (Kumar et al. 2011). The Pacific Northwest and West Coast has the most abundant hydropower resources in the U.S., with California, Washington, Alaska, Idaho and Oregon having the largest technical potential of all states (Lopez et al. 2012).

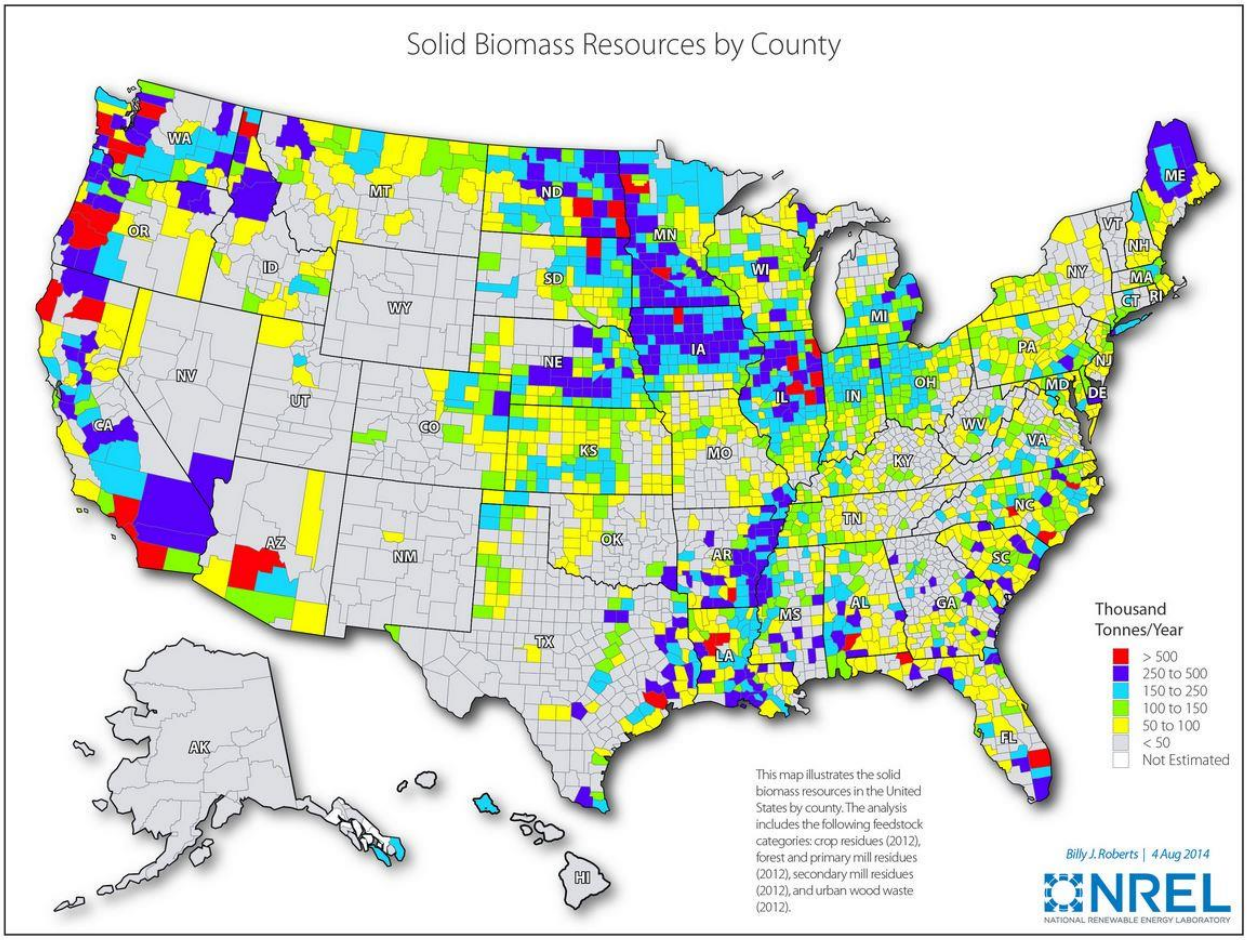
Solar energy is generated by harnessing the energy of radiation from the sun that is intercepted by the earth. Solar energy can be used to generate electricity either through the use of photovoltaic cells or by heating fluids and producing steam with solar concentration facilities (Arvizu et al. 2011). The technical potential of solar energy generation depends on the available solar irradiance, land use factors and future developments in technology (Arvizu et al. 2011). The amount of solar irradiance varies significantly by region because of differences in latitude and climate. The solar PV resources in the U.S. are most abundant in the Southwest states of Arizona, New Mexico, Colorado and Utah, and southern California and southern Nevada (Roberts 2012).

Geothermal energy is generated using wells to utilize the heat within the earth's crust to produce hot fluids that can be used for heating or to produce electricity with steam turbines (Goldstein et al. 2011). Regional variation in technical potential depends on geothermal gradients, with high temperatures associated with volcanism and tectonic plate boundaries. Based on temperature data from depths between 3km and 10km deep within the earth, geothermal resources are generally more abundant throughout the Western US, than in the east (Roberts 2009).

Wind energy is produced when the kinetic energy from wind is harnessed by spinning turbines. The technical potential of wind energy is determined by the prevalence, consistency, and speed of winds, and land-use constraints (Wiser et al. 2011). Annual average wind speeds in the U.S. are highest in a corridor that runs through the central portion country, often referred to as tornado alley. Significant wind resources also exist off-shore on both coasts (NREL 2015).

The technical potential of biopower varies by region as a result of variation in the availability of feedstocks. However, as seen in figure 2.1, which displays the distribution of solid biomass resources across the U.S by county, the availability of biomass feedstocks is not limited to one particular region of the country. Although figure 2.1 does not break down the feedstocks by type, in feedstock-specific maps it is apparent that the availability of agricultural crop residues is highest in upper Midwest states like Minnesota and Iowa, but numerous other states have significant amounts of crop residues as well (Roberts 2014b). Forest residues and residues from primary and secondary mills are most abundant in forested areas with timber harvesting activity like the Pacific Northwest, Northeast and Southeast (Roberts 2014c). One potentially significant source of biomass feedstocks in the Western US that it not accounted for in figure 2.1 is timber from forest treatments on public timberland, of which around 576 million bone dry tons exists on the 28.5 million acres that could benefit from treatment (Rummer et al. 2005).

Figure 2.1. Technical Potential of Biopower: Solid Biomass Resources by County



Source: Roberts (2014a)

2.1.2 Financial Cost of Production

While financial costs of production is not the only fact that determines investment decisions in different energy generation projects (policy factors, and existing regional energy mixes and available energy resource are important considerations), it is a major driver of decisions about how much energy gets produced from different sources. The levelized cost of electricity (LCOE) is a convenient measure of the overall financial competitiveness of different energy generation technologies (EIA 2014a). LCOE represents the per-kilowatt-hour cost of building and operating a utility-scale power plant over its lifetime, taking into account: capital costs, fuel costs, fixed and variable operations and maintenance (O&M) costs, and financing costs (EIA 2014a). In the *Annual Energy Outlook 2014*, the US Energy

Information Administration presents estimated average values of levelized costs for energy generation systems coming online in 2019 (Table 2.3).

Geothermal energy has the lowest total LCOE of all renewable energy options, and in fact has a lower total LCOE than both coal and natural gas. Geothermal has the lowest capital investment costs and no variable O&M costs because it does not rely on a fuel feedstock to generate power. Wind has the second lowest total LCOE of the renewable energy technologies, and is also lower than coal. While capital costs for wind are double that of geothermal, it too has no variable O&M costs, which contributes to its low total LCOE. Hydropower has the third lowest total LCOE amongst renewable energy alternatives. Hydropower's capital costs are higher than all technologies other than solar PV and has the second highest variable O&M costs, but also has the lowest fixed O&M costs of all renewable options. Solar PV has the highest total LCOE of all energy technologies. Although it has zero variable O&M costs, it's very high capital investment costs drive up total LCOE.

Biomass energy has the second highest total LCOE of all renewable energy options. Although capital investment costs are lower than all but geothermal, biomass has variable O&M costs that are much higher than all other renewable energy technologies. Although other factors contribute to variable O&M costs, high variable O&M costs for biomass are likely being driven by the cost of feedstock based on the fact that harvesting, collecting, processing, storing and transporting woody biomass feedstock can be quite expensive and typically drives the financial cost of production Keefe et al. (2014). Furthermore, materials that are more efficient to handle, such as small diameter logs, often have alternative markets that offer higher value than energy, such as posts and poles, wood pulp and panels. The high costs of obtaining feedstock can limit the financially viable area from which biomass energy plants can obtain feedstock. This limits opportunities to benefit from economies of scale that exist for other renewable energy generation types (Morris 1999). Based on these insights, financial competitiveness will not be the driving factor for increased production of biomass energy, but it is not strictly dominated by other renewable energies across the board.

It is also interesting to note that three of the renewable energy technologies have lower total LCOE than both coal and natural gas, suggesting that the common adage that renewable energy cannot compete financially with fossil fuel energy does not hold true in all cases.

Table 2.3. Estimated Levelized Costs of Energy Production, 2019 ($/MWh)

Rank	Energy Type	Total LCOE	Capital	Fixed O&M	Variable O&M (including fuel)	Transmission investment
1.	Geothermal	47.9	34.2	12.2	0.0	1.4
2.	Wind	80.3	64.1	13.0	0.0	3.2
3.	Hydropower	84.5	72.0	4.1	6.4	2.0
4.	Biomass	102.6	47.4	14.5	39.5	1.2
5.	Solar PV	130.0	114.5	11.4	0.0	4.1
	Fossil Fuels					
	Natural Gas	66.3	14.3	1.7	49.1	1.2
	Coal	95.6	60.0	4.2	30.3	1.2

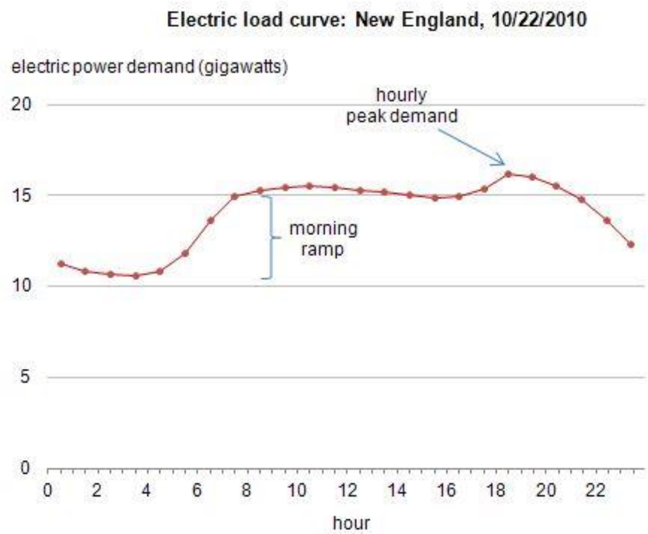
Source: EIA (2014a)

Note: Values for natural gas represent a conventional combined cycle system

2.1.3 Base-Load and Peak-Load Power

Power demand in the US fluctuates daily and seasonally. Figure 2.2 illustrates the daily trend of electric power demand at its lowest in the early hours of the morning, experiencing a morning ramp, and peaking in the early evening (EIA 2011b). Peak demand also varies seasonally with the weather, peaking in mid-summer and mid-winter as a result of changes in demand for heating and cooling (EIA 2013c). The minimum amount of electric energy required over time at a steady rate is known as base-load and the highest spikes in demand are known as peak-load (EIA 2010).

Figure 2.2. Daily Fluctuation in Electricity Demand



Source: EIA (2011b)

Because it is not possible to store significant amounts of energy, a mixture of base-load and peak-load plants are needed in order to supply both the constant base-load demand for energy and the daily and seasonal peaks in demand. Conventional power plants such as coal and nuclear that generate energy by creating steam that spins turbines can supply base-load power by operating around the clock to supply a continuous quantity of electricity that matches the base-load demand of an energy system (EIA 2015b).

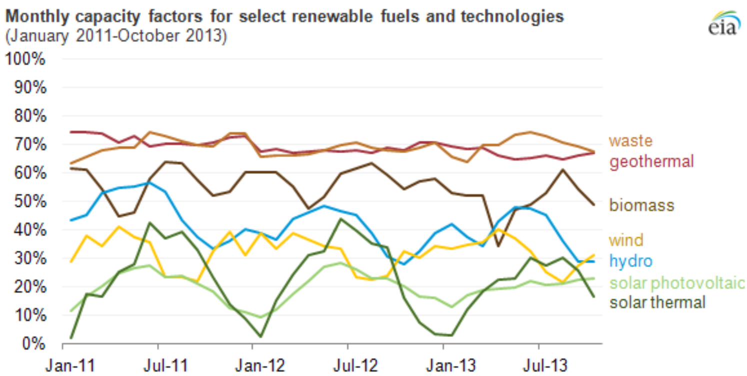
Base-load plants are cheap to operate but have high capital costs and can take hours or days to fire up from cold (Diesendorf 2007). As a result, they are not efficient to use as peak power plants, which requires the plant to sit idly for significant amounts of time. To supply peak energy demand, power stations with high operating costs, but low capital costs and short start-up times such as natural gas combustion turbines are most efficient (Diesendorf 2007). A third type of power plant exists which can serve to bridge the gap between base-load and peak-load power plants. These intermediate load plants have output that is more readily changed than base-load but not as flexible as peak-load, and have operating costs in between base load and peak-load (Diesendorf 2007).

The ability of energy generation systems to produce a continuous supply of energy is evaluated using a measure called capacity factor. Capacity factor is the ratio of electrical energy produced by a power plant over a period of time to the electrical energy that could have been produced at continuous full power operation during that period (EIA 2015b). A power generation plant that operated continuously with no interruptions would have a capacity factor of 100%. Intermittent power sources output electricity at a rate that is controlled by the natural variability of the energy resource, rather than by energy demand and system requirements and as a result, have lower capacity factors (EIA 2015b). Energy sources do not need to have a high capacity factor to effectively supply energy at times of peak demand. Instead, it is most favorable to have controllable output with short start up times so they can be ramped up to meet demand.

Because energy generation must be scaled to meet both base-load, and peak demand in real time, a mix of base-load, peak-load, and intermediate-load power plants is needed to provide an efficient supply of energy. Which type of generation each renewable energy source is most suited for depends on: capacity factors, ability to control timing of production, capital costs, operation costs, and the amount of time it takes to start-up production. A high capacity factor and low operating costs indicate an energy source well suited to supplying base-load power. Low capital costs, fast start-up times and the ability to control timing of output make an energy source well suited to provide peak-load power. Renewable energy technologies with variable or intermittent output can also effectively supply peak-load power if their availability naturally coincides with times of peak demand.

Solar PV energy generation is an intermittent power source whose output is dependent on the presence of sunshine, which depends on the time of day, season and weather patterns. Solar PV energy has the lowest capacity factor of all renewable sources (Table 2.3), and is therefore not very well suited to provide base-load power. However, the real-time availability of solar does coincide well with peak afternoon electricity demand, allowing it to serve as a useful generator of peak energy during these times (NREL 2013b). Additionally, solar resources are most abundant in the summer, which coincides with seasonal peak demand, and provides the ability to supply energy during peak summer demand (Figure 2.3). These characteristics also make solar an appropriate intermediate-load power source for filling the gap between base-load and peak-load during the daytime.

Figure 2.3. Monthly Capacity Factors for Renewable Energy Sources



Source: EIA (2014)

Wind power is an intermittent and variable energy source that can only be generated when the wind is blowing. Wind energy has the second lowest capacity factor of all renewable energy sources and is not as well suited to supply base-load power as geothermal, biomass or hydropower. However, although the timing of production for a single wind turbine is highly variable, when aggregated over many turbines and multiple production sites, the variability becomes significantly more predictable (NREL 2015). As a result, wind can still provide base-load power, as long as sufficient back up power from natural gas turbines exists (Diesendorf 2007). Because wind power cannot be fired up and shut down in response to peaks in demand, it is not very appropriate for use as a peak-load energy supply source.

Hydropower has a capacity factor that is higher than both wind and solar, but lower than biomass and geothermal. Hydropower from plants that harness the energy of water stored above dams in reservoirs is available continuously and can be used to supply base-load power. Because the resource is available around the clock and hydroelectric stations do not have long start-up times, hydroelectric can also be used to supply peak-load power. Geothermal energy has the highest capacity factor of all the energy options, has low operating costs[2], and does not vary daily or seasonally. These characteristics make geothermal energy ideally suited for base-load power production.

Biomass energy has the second highest capacity factor of renewable energy sources which is a good characteristic for base-load power production. Because feedstocks can be stockpiled and stored, biomass energy is not dependent on the real time availability of the resource like solar PV or wind energy and can be used to generate energy around the clock. However, the highest operating costs amongst all energy options (Table 2.3) are a drawback. The fact that biomass energy has the second lowest capital costs amongst renewable energy options (Table 2.3) is an attractive characteristic for peak-load power, depending on how quickly biomass power plants can be started up from cold.

Table 2.4. Average Annual Capacity Factors USA, 2014

Rank	Energy Type	Capacity Factor (%)
1.	Geothermal	92%
2.	Biomass	83%
3.	Hydropower	53%
4.	Wind	35%
5.	Solar PV	25%
	Conventional Base-load	
	Nuclear	90%
	Coal	85%
	Natural Gas	87%

Source: EIA (2014a)

Note: Values for natural gas represent a conventional combined cycle system. The capacity factor for natural gas advanced combustion turbine, like would be used to supply peak-load power is 30%.

2.1.4 Life Cycle Assessment

[2] From table 2.3, total O&M costs = 12.2 \$/megawatt-hour. This is lowest amongst renewable energy technologies.

Life cycle assessment (LCA) is used to determine the "cradle to grave" environmental burden of energy systems by tracking all material, energy, and pollutant flows of the system – including raw material extraction, manufacturing, transport, construction, operation and waste disposal (NREL 2013a). By accounting for all potential sources of emissions, LCA provides a consistent framework to evaluate the environmental impacts of any given pollutant produced during the various stages of an energy production system. A major use of LCA for energy generation systems is the assessment of the global warming impacts of each unit of energy produced, whichis discussed in this section. In their special report *Renewable Energy Sources and Climate Change Mitigation,* the Intergovernmental Panel on Climate Change (IPCC) produced a meta-analysis of hundreds of LCA estimates for renewable and conventional energy sources from the published literature (Edenhofer et al. 2012). The significant variability that exists in the estimates arises from both factors related to the diverse methodologies used to generate the estimates and from diversity in the generating technologies for each energy source (Sathaye et al. 2011).

Results from the IPCC meta-analysis, presented in Table 2.5, reveal that hydropower emits the lowest median number of grams of CO_2 equivalent per kilowatt hour (gCO_2eq/kWh). Wind power has the second lowest median value, followed by biopower, geothermal, and solar PV. Assessing the global warming impacts of bioenergy involves considerable uncertainty because estimates are sensitive to a number of factors that vary for different conversion technologies, feedstocks and site-specific environmental conditions (Chum et al. 2011). Because the IPCC meta-analysis includes LCA estimates that cover different conversion technologies and feedstocks, a general comparison between bioenergy and other energy technologies is conducted.

The considerable uncertainty associated with estimates for biopower can be seen in the large range that exists between the minimum and maximum estimates in the literature (estimates range over 700 gCO_2eq/kWh). Based on median values from the LCA meta-analysis, energy produced with biopower is in the middle of the pack of renewable energy sources in terms of climate change impacts. However, the significant variation in estimates highlights the sensitivity to case-specific factors and assumptions.

The fact that biopower has more favorable LCA numbers than geothermal and solar PV is likely a surprising result to many, but it should be noted that the range between median values of the top ranked renewable (wind), and the bottom ranked renewable (solar PV) is only 42 CO_2eq/kWh. The numbers each of the renewable energy options are much lower than the median values of 469 CO_2eq/kWh for natural gas, 840 CO_2eq/kWh for oil, and 1001 CO_2eq/kWh for coal. As a result, perhaps the most illuminating piece of information that can be drawn from Table 2.5 is that every renewable energy option offers significant climate change mitigation benefits relative to fossil fuel energy options.

Table 2.5. Life-cycle GHG emissions in grams of CO_2 equivalent per kilowatt hour (gCO_2eq/kWh)

Rank (based on median)	Energy Type	Minimum	Median	Maximum
1.	Hydropower	0	4	43
2.	Wind	2	12	81
3.	Biopower	-633	18	75
4.	Geothermal	6	45	79
5.	Solar PV	5	46	217
	Fossil Fuels			
	Natural Gas	290	469	930
	Oil	510	840	1170
	Coal	675	1001	1689

Note: 1. The report notes that negative values for biomass are possible due to avoided emissions, like when using waste results in avoided methane emissions from landfills. The report did not explain why this minimum value for biomass was so much lower than the minimum for other energy sources.
Source: Moomaw et al. (2011)

2.1.5 Non-Market Costs and Benefits

Producing energy using any one of the renewable energy sources discussed so far also has associated environmental and social effects. These effects can be positive or negative, are different for each energy type, and can vary by site and region because of site-specific characteristics and regional differences in geography and socioeconomic characteristics. Because markets typically do not exist that allow the costs and benefits associated with these effects to be internalized, externalities are created which impact social welfare. In addition to local air pollution and acid rain, among the most well-known externalities associated with energy generation is global climate change which is being caused by the greenhouse gases that are emitted into the atmosphere by the burning of fossil fuels. The biggest benefit provided by all types of renewable energy generation is the ability to offset fossil fuel energy generation and the greenhouse gas emissions associated with it. The rest of this section describes the other environmental and social impacts associated with each renewable energy source because the non-market costs and benefits associated with externalities are an important component in assessing the socioeconomic efficiency of energy generation alternatives.

The main environmental effects associated with utility-scale solar PV energy generation are the use of toxic materials in the production of photovoltaic panels, and land consumption and its impacts on local flora and wildlife (Arvizu et al. 2011). In addition to impacts related to land consumption associated with solar PV, solar thermal plants that use water to cool their steam turbines can increase competition for scarce water resources (Arvizu et al. 2011). Negative impacts associated with photovoltaic panels can be minimized through recycling and water use issues can be mitigated through the use of dry cooling systems (Arvizu et al. 2011). The main potential negative effect of utility-scale solar energy facilities is visual impacts to landscapes (Arvizu et al. 2011). These impacts can be minimized through choosing sites in areas with low population density and avoiding conservation areas (Arvizu et al. 2011). Positive social effects of solar energy generation can include providing electricity to rural and isolated communities that are not connected to centralized electric grids (Arvizu et al. 2011).

Utility-scale hydropower stations can rely on reservoir-creating dams, or run-of-river dams that do not significantly alter river flow regimes (Kumar et al. 2011). The majority of negative impacts of hydropower projects are caused by the creation of reservoirs which alter flow regimes in terms of timing and levels of flows; disrupt erosion, transportation and disposition of sediments; and alter water temperatures. All of these disruptions to river systems damages aquatic ecosystems and habitat (Kumar et al. 2011). Dams also physically block fish passage and have contributed to the decline in some species, like salmon in the Western US, by cutting off upper reaches of watersheds that migratory fish rely on as spawning habitat (Raymond 1979). Reservoir creation can also provide benefits in the form of flood control services and water storage for irrigation, and municipal and industrial uses (Kumar et al. 2011).

The biggest ecological concern related to wind energy generation is the potential for bird and bat fatalities through collisions with wind turbines (Wiser et al. 2011). It is uncertain what the population level impacts of these fatalities might be and fatality rates can vary by site, season, and turbine size and design (Wiser et al. 2011). As with solar installations, wind farms require significant amounts of land, which can modify ecosystems, although the degree of damage that this may cause is uncertain (Wiser et al. 2011). Social impacts of wind energy can arise from the noise pollution sometimes created by turbines, which can be annoying and potentially cause health impacts on human populations living in close proximity to installations (Wiser et al. 2011). Visual impact on landscapes is another potential negative social impact of wind energy (Wiser et al. 2011). However, similar to solar, social impacts of wind energy can be mitigated by siting wind farms in areas with low population density (Wiser et al. 2011). The negative environmental impacts of geothermal energy are generally considered to be minor, but potential effects include ground subsidence and induced seismic activity (Goldstein et al. 2011).

The environmental and social impacts associated with biomass energy vary according to the type energy being generated and the type of feedstock, as well as geographic and site-specific characteristics (Chum et al. 2011). Negative environmental impacts associated with crop-based bioenergy can include: impacts on water resources through increased fertilizer runoff; impacted air quality, biodiversity and habitat loss from the conversion of natural ecosystems to cropland and impacts on soil resources from sediment runoff and nutrient leaching (Chum et al. 2011). A major socioeconomic concern with crop-based bioenergy is the risk to food security from increased competition for food crops (Chum et al. 2011). Energy generated with forest biomass has associated environmental and socioeconomic effects that are distinct from those associated with crop-based bioenergy (Chum et al. 2011).

Forest fuels reduction treatments that can produce biomass for energy reduce the severity of large wildfires in ponderosa pine and mixed conifer forests (Agee and Skinner 2005, Stephens et al. 2009). These treatments can reduce the risk of damage to watersheds, and to homes and other structures when placed near communities in the wildland urban interface (Ager et al. 2010). When associated with forest restoration treatments, increased biomass harvest can result in increased amounts healthy forests that support a greater diversity of native plant and animal species and are more resilient to human and natural disturbances like insect outbreaks, non-native invasive species, disease, wildfires and a changing climate (Swanson et al. 1994, Barrett et al. 2012). Because residues have historically been disposed of by burning onsite, positive impacts on air quality can occur when materials that would have been burned in the open are instead combusted in a controlled environment during energy generation (Jones et al. 2010).

The harvest of forest biomass can also result in the loss of habitat for forest species that rely on the presence of coarse woody debris (Chum et al. 2011). Water quality and aquatic ecosystems can be negatively impacted through increased traffic on forest roads which increases sediment flux into streams and lakes (Waters 1995). It is also worth pointing out that some sources of woody biomass for energy, including whole tree harvesting and land clearing for land conversion to agriculture, development and other non-forest uses, can have negative carbon consequences compared to using treatment residues. Impacts on air quality from bioenergy production are heavily dependent on energy conversion technology, fuel source, fuel properties, and emissions controls, but generally there can be NO_x, SO_x and particulate matter emissions associated with bioenergy production that can negatively impact air quality (Chum et al. 2011).

2.2 Role for Woody Biomass - Opportunities and Challenges

About 2% of US energy generation presently comes from woody biomass (EIA 2010), and studies have found that woody biomass could eventually supply up to 10% of US energy needs (Zerbe 2006). While industrial mill residues have historically accounted for the majority of woody biomass energy in the US (Malmsheimer et al. 2008), forest residues provide a significant amount of potential future feedstock. There are over 28 million acres of forestland in the Western US that are severely departed from historic fire regimes and could benefit from mechanized fuels reduction treatments (Rummer et al. 2005). The mechanized treatment of all 28 million acres could result in the removal of 576 million dry tons of biomass. Assuming that 30% of the removed biomass is residues (U.S. Department of Energy 2011), 173 million dry tons of residues could be produced by mechanized thinning of forestland that is severely departed from historic reference conditions. Nationally, the level of forest biomass consumption has been forecast to increase from the current level of 129 million dry tons per year to 226 million dry tons in the year 2030 (U.S. Department of Energy 2011).

However, the role that woody biomass plays in the mix of energy generation sources depends on more than the amount of biomass resource that is physically available. Bioenergy operations must also be financially viable, and costs associated with of harvesting, transporting, processing, and converting the biomass into energy are often prohibitively expensive. For example, while Beringer et al. (2011) estimated that 15-25% of global primary energy could come from bioenergy in 2050, and Tilman et al. (2009) found that bioenergy from forests could substantially diminish dependence on fossil fuels, Lauri et al. (2014) found that while the global woody biomass resource is large enough to supply up to

40% of the world's energy consumption, only approximately 9% of world primary energy consumption was supplied by wood in 2010, due in part to prohibitively high costs.

2.2.1 Financial & Logistical Considerations

The financial feasibility of woody biomass energy generation depends on both the price at which biomass is demanded and supply side costs associated with acquiring, processing, and transporting the biomass. The market price of biomass feedstock is a critical determinant of financial feasibility of the technology (Han et al. 2004, Jones et al. 2013), and has been found to be a barrier to bioenergy operations (Pan et al. 2007). In the US, when the price is less than $20 per dry ton only 33 million dry tons of biomass are available, but when it moves to $30 per dry ton, the amount available more than doubles to 70 million dry tons (U.S. Department of Energy 2011). The market price and availability of biomass can be influenced by competition for resources from other biomass users like pulp mills (Sedjo 1997). Sometimes however, no markets exist for the biomass and a lack of markets has inhibited utilization in the Western US (Jones et al. 2013). The market price of other energy sources also affects the feasibility of woody biomass energy operations (Sedjo 1997). For maximum feasibility, the price of biomass feedstock would be in a sweet spot that is low enough to compete with other forms of energy generation, but high enough for biomass energy producers to compete the resource away from other users (Sedjo 1997).

Important financial costs associated with woody biomass energy generation include: production and logistic costs, capital costs of power plant by scales, operation and maintenance costs, labor costs, capital financing costs and other regulatory costs (Upadhyay et al. 2012). The cost of removing the biomass from the forest is driven by logistical considerations, which are a key driver of the financial feasibility of using woody biomass for energy generation. Although the acquisition cost of the biomass is often very low, harvesting, collection, processing, storage and transportation can be quite expensive and can result in costs that exceed the delivered value of the feedstock (Keefe et al. 2014). Multiple methods exist for each logistical step in the supply chain and selecting the optimal method for the operation at each step can greatly improve the economic feasibility of the feedstock supply (Keefe et al. 2014). The supply chain varies according to land ownership, management objective, forest stand characteristics, and end use of the biomass (Keefe et al. 2014). All of these factors will influence the optimal method for each step in the supply chain.

Logistics costs are influenced by harvest site characteristics such as, forest productivity and the steepness and accessibility of terrain (Eriksson and Gustavsson 2010). These characteristics can influence the optimal choice of harvest systems and residue recovery methods. The choice of harvesting system has a significant effect on the cost of biomass recovery (Mangoyana 2011). In flat and moderate terrain, either whole-tree or cut-to-length ground-based methods can be employed. Using whole-tree harvesting, residues are concentrated at the landing. When using cut-to-length methods, additional equipment is required to forward the residues to the landing used because residues are scattered throughout the harvest site. In terrain that is too steep for ground-based logging, cable-based methods or helicopter harvesting methods are used. Harvesting costs are higher for smaller-diameter trees, like those that are predominantly removed in thinning operations, especially if cable-based or helicopter systems are used (Han et al. 2004).

Biomass residues must be comminuted through chipping or grinding before they can be used for energy generation. Whether to use chipping or grinding is partially determined by the end use of the biomass because each energy generation technology has unique requirements for the size, shape, consistency, moisture content and quality of feedstock. Comminution can be done roadside in the woods, or after transportation to a concentration yard. The decision about where commination will take affects costs because comminuting the residues in the woods may be more expensive than in a centralized location, but it concentrates the biomass and reduces transportation costs (Anderson et al. 2012).

In the Western US, haul distances are often long and can be a major component in supply costs. In fact, it can represent the largest component of logistic costs (Pan et al. 2007). The cost of transportation fuels significantly affects the cost of transportation and the financially feasible area of supply for a bioenergy facility (Han et al. 2004, Jones et al. 2013). In addition, forest roads can limit the type and size of truck that can be used (Jones et al. 2013). In the selection of transportation method, tradeoffs must be made between the capacity of the transport vehicle and their maneuverability on tight forest roads. To maximize efficiency, a combination of smaller and larger transport vehicle may be used (Keefe et al. 2014).

2.2.2 Public Policy in the US and Internationally

According to the Union of Concerned Scientists, one of the major barriers to renewable energy technologies is market price distortions created by unequal subsidies and tax burdens between renewable and fossil fuel energy sources. One of the most crucial aspects that can limit the ability for growth in the wood energy sector, and other renewable energies, is the presence of inexpensive fossil fuel alternatives. Globally, at $557 billion in 2008, the subsidization of fossil fuels is an order of magnitude greater than subsidization of renewable energy (IEA 2010) (BNEF 2010).

As a result, policy support is an essential element for the growth of renewable energy generation and the existence of public policies plays an instrumental role in the development of the bioenergy industry. In addition to the state-level renewable portfolio standards, there are national-level policy instruments in the US that encourage bioenergy. These policies work through both financial incentives and by mandating actual amounts energy that must be supplied with renewable sources.

The US Energy Policy Act of 2005 and its 2007 amendment mandate the use of renewable energy, including encouraging bioenergy. Specific provisions in regards to bioenergy include a mandated increase in the amount of biofuels to be mixed with gasoline, providing loan guarantees for innovative technologies that avoid greenhouse gas production (including bioenergy), and authorizing $50 million annually for biomass grants. Agricultural legislation has also been used to create energy policies. The Biomass Crop Assistance Program provides financial assistance to private agricultural landowners and non-industrial private forest owners. Landowners receive matching payments for the delivery of feedstock to thermal, electrical and biofuel facilities.

Despite these policies, the share of bioenergy in the US energy mix is significantly lower than many countries in the European Union and elsewhere in Europe. Woody biomass energy consumption in the EU more than doubled between 1990 and 2010, which has been attributed to ambitious targets to reduce greenhouse gas emissions by 20%, increase energy efficiency by 20%, and for 20% of energy consumption to be generated from renewable sources by 2020Lantiainen et al. (2014)). It is expected that by 2020, biomass will account for 45% of heat and power production in the EU (Flach et al. 2014).In Sweden, bioenergy use represented 27% of all energy production in 2006 (Mangoyana 2011). The significant role that it plays in Sweden's energy mix has been attributed in part to policy instruments such as market support, green certificates, carbon trading, heavy carbon taxes, subsidies for clean energy development and climate change investment programs (Mangoyana 2011).

2.3 Non-Market Costs and Benefits of Utilizing Woody Biomass for Energy

There are potential positive and negative environmental effects associated with the harvest and utilization of woody biomass for energy generation. These effects can create nonmarket costs and benefits that affect the socioeconomic efficiency of woody biomass energy. The potential effects on forest health, wildfire risk, air quality, and the climate are described in the following sub-sections.

2.3.1 Forest Health

Biomass may be harvested from a wide variety of forest management systems and the implications for sustainability and forest health differ for each system and across forest types (U.S. Department of Energy 2011). Dead wood serves many important ecological functions, including serving as habitat for a variety of organisms, reducing runoff, and replenishing soil nutrients (U.S. Department of Energy 2011). The removal of this dead wood through biomass harvest can result in changes in forest structure (Berger et al. 2013), reduced soil productivity (Thiffault et al. 2011), and increased sediment runoff into streams (Shepard 2006). These effects can negatively impact biodiversity in both terrestrial and aquatic ecosystems (Berger et al. 2013). However, the magnitude of these potential impacts can vary depending on site characteristics, and the intensity of biomass harvest (Berger et al. 2013). Negative impacts can be mitigated through the use of best management practices designed to minimize negative environmental impacts (Abbas et al. 2011, U.S. Department of Energy 2011).

Restoration is needed in many forests throughout the Western US, as a result of the transformation of the forested landscape that has resulted from livestock grazing, selective logging of old growth trees, fire suppression, and extensive road building (Brown et al. 2004, Ryan et al. 2013). These forests commonly exhibit increased tree density, structural homogenization, and fuels buildup (Taylor 2004).

There are numerous potential metrics that can be used to assess ecosystem conditions and the appropriate definition of forest health depends in part on management objects. A commonly used metric is historical range of variability (HRV), a measure of departure of ecosystem conditions from before the time of Euro-American settlement in North America (Veblen 2003). According to the HRV metric, forests that are departed from within the range of historic reference conditions are considered to be unhealthy. The specific management actions required to achieve desired conditions varies across different places and forest types with different historic fire regimes, but generally a combination of mechanized thinning and prescribed burning can be used (Brown et al. 2004).

Therefore, when associated with forest restoration or mechanized thinning treatments, woody biomass harvest can have a positive effect on forest health. Healthy forests are more resilient to human and natural disturbances like insect outbreaks, non-native invasive species, disease, wildfires and a changing climate (Swanson et al. 1994, Edmunds et al. 2000).They are also more able to support native plant and animal species (Huntzinger 2003, Hiers et al. 2007, Barrett et al. 2012).

2.3.2 Wildfire

Overgrown and structurally homogenous forests are and more likely to experience unusually severe and damaging wildfires (Schwilk et al. 2009). Some forestland can be treated with prescribed fire alone, but in cases where very high fuel loads are present, air quality restrictions are in place, or the forest is in close proximity to developed areas, mechanized treatments may be required before, or in place of, prescribed fire (Rummer et al. 2005). Mechanized thinning treatments can also reduce the likelihood and severity of large wildfires (Stephens et al. 2009), that can threaten numerous human and ecological values (Graham et al. 2004). Thinning treatments can reduce fire intensity and severity by using heavy equipment to remove ladder fuels, like small trees and shrubs, that allow surface fires to climb into the forest canopy (Graham et al. 2004). For maximum efficacy and longevity, mechanized thinning can be combined with prescribed fire to reduce canopy, ladder, and surface fuels (Graham et al. 2004).

2.3.3 Air Quality

Woody biomass energy facilities can emit particulate matter and other pollutants (Jonsson and Hillring 2006). In communities where woody biomass energy generation facilities are located, local air quality may be negatively impacted (Chum et al. 2011). These types of emissions have been shown to negatively impact human health (Pope et al. 2002, Pope et al. 2009). However, the efficiency the energy plant is a significant determinant of emissions (Boman et al. 2003) and modern, efficient facilities emit fewer pollutants than older plants (Jonsson and Hillring 2006).

The utilization of woody biomass for energy generation can also have positive impacts on air quality. Residues are often disposed of through pile-burning in the woods, releasing emissions into the air unfiltered, including particulates and gaseous products of incomplete combustion, such as methane (Loeffler and Anderson 2013). When combusted in a controlled environment for energy generation instead, these emissions are reduced (Jones et al. 2010). Wildfires also emit large amounts of particulate emissions (Rittmaster et al. 2006, Rittmaster et al. 2008). Because fuels reductions treatments reduce the likelihood of large wildfires, the utilization of residues for energy generation can also improve air quality by reducing the amount of smoke generated by wildfires.

2.3.4 Climate change

Woody biomass energy offers potential climate change benefits by offsetting some fossil fuel carbon emissions with biogenic carbon emissions. However, there is debate in the scientific literature over the carbon neutrality of forest-based bioenergy. Biogenic emissions do not add any new carbon to the system of carbon cycling that occurs between the atmosphere and terrestrial biosphere (Figure 2.4). Fossil fuel emissions on the other hand, add geologic carbon into the biosphere that is cannot be sequestered back into their geologic stock, thus increasing atmospheric carbon concentrations in the long run. Some have argued that what matters is this level of carbon in circulation in the biosphere as a whole, as opposed to the atmosphere alone (Lippke et al. 2010).

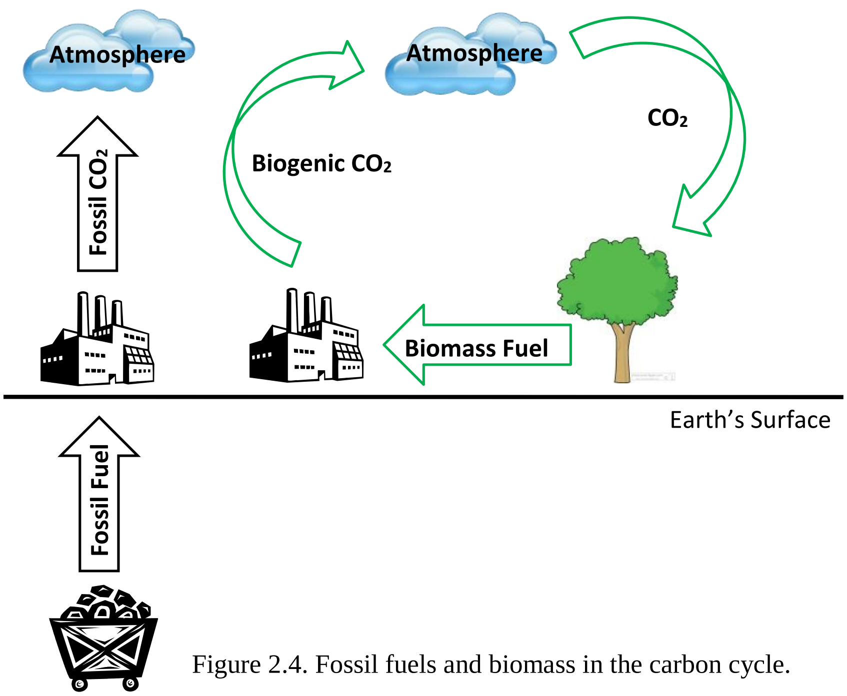


Figure 2.4. Fossil fuels and biomass in the carbon cycle.

Debate over the carbon neutrality of bioenergy arises when biomass is harvested specifically for energy generation. Under sustainable management practices, the biogenic carbon emissions are sequestered in biomass regrowth over time and forest bioenergy is usually close to C neutral over the rotation time of the stand from which the biomass was harvested. However, the temporal imbalance of atmospheric carbon that may arise because of the higher per unit carbon emissions from woody biomass energy than from the fossil fuels that may be displaced, the fossil fuel emissions associated with the harvesting and processing of the biomass, and the foregone carbon sequestration that would have occurred had the biomass not been harvested. Based on these factors, some studies have found that replacing fossil fuels with bioenergy does not generate lower atmospheric concentrations of carbon in a timeframe that is relevant for addressing climate change (Searchinger et al. 2009, McKechnie et al. 2010, Hudiburg et al. 2011, Gunn et al. 2012). Others question the climate change benefits of bioenergy because of potential land use change and increases in overall intensity and frequency of harvests that may result in managing forests for biomass harvesting for energy (Gunn et al. 2012).

On the other hand, some studies find that offsetting fossil fuels with bioenergy provides carbon balance benefits because more forest carbon stocks may actually increase as a result of biomass harvest (Daigneault et al. 2012, Sedjo and Tian 2012), or because in the long-term, the accumulating benefit of fossil fuel substitution dominates the short-run carbon balance effects (Sathre and Gustavsson 2011, Pingoud et al. 2012). Investigations of the utilization of forest residues specifically, are in consensus that there are no negative short-term carbon balance effects associated with the utilization of residues for energy generation (Gustavsson et al. 1995, Jones et al. 2010, Sathre and Gustavsson 2011).

2.4 Summary

The topics discussed in this chapter highlights that there are opportunities and challenges associated with the expansion of woody biomass energy generation in the US. Woody biomass energy has strengths and weaknesses relative to other sources of renewable energy. The ability to supply power around the clock makes it attractive as a source of base-load power, compared to intermittent renewable energy sources. Climate implications of woody biomass energy relative to other renewable energy sources are somewhat unclear. Life-cycle GHG emissions estimates associated with biomass energy have a large range and are sensitive to assumptions about the neutrality of biogenic carbon emissions. There are environmental effects associated with each renewable energy source and, in order to compare the magnitude of these effects, the associated nonmarket costs and benefits need to be quantified.

At a national level, the technical potential of woody biomass energy is low relative to solar, wind and geothermal energy, which will constrain the upper limit of the portion of national energy demand it can supply. There are, however, large amounts of forest residues that currently are not utilized that could be used to generate energy, and there are potential environmental benefits associated with the utilization of those residues. High harvest, processing and transportcosts sometimes make the utilization of the residues financially infeasible. However, the potential environmental benefits associated with woody biomass energy may make woody biomass more attractive from a socioeconomic efficiency perspective. Public policies that support renewable energy make a difference in the viability of renewable energy generation, as illustrated by the rapid growth in woody biomass energy generation associated with the aggressive renewable energy requirements in Europe.

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Chapter 3

General Methods

In order to demonstrate the utility of the choice modeling method for investigating the socioeconomic efficiency of woody biomass energy, this chapter provides an overview of nonmarket valuation techniques and the conceptual framework on which they are based. The chapter begins by describing the conceptual framework for nonmarket valuation. Then the multiple methods that exist are presented briefly, and choice modeling is described in detail. Finally, the measures of economic worth that can be estimated using nonmarket valuation are described and their usefulness in policy making is explained.

3.1 Conceptual Framework for Nonmarket Valuation

The concepts and techniques employed in nonmarket environmental valuation are based upon multiple concepts and models of economic theory. This section introduces the essential concepts required to approach an environmental problem using an environmental economic framework. First, the concept of economic value is introduced, and then the topics of property rights and market failure are discussed. Finally consumer theory and how it allows for the quantification of economic welfare measures is explained.

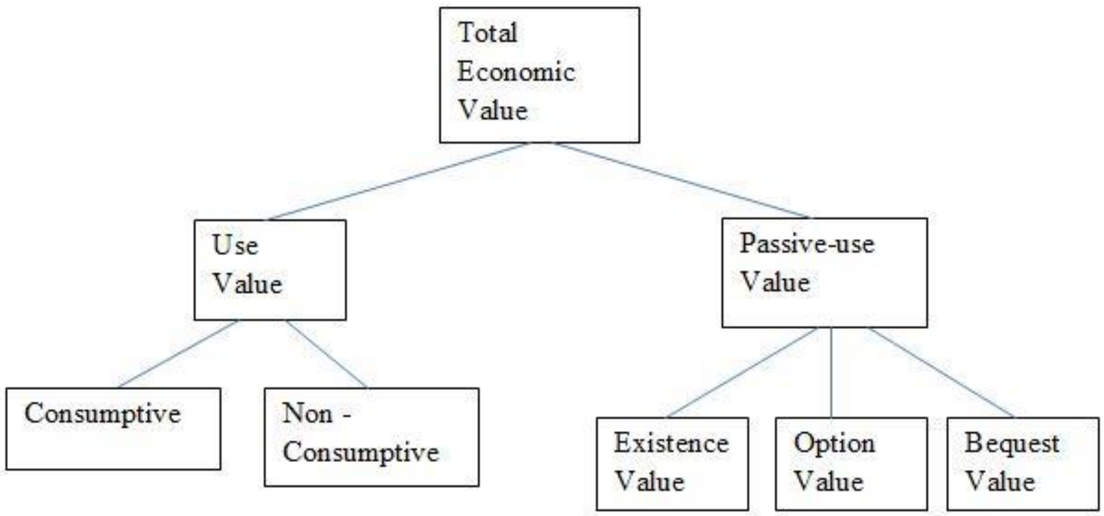
3.1.1 Economic Value

In an environmental economic framework, the natural environment has value because of the goods and services it can provide that contributes to human well-being (Freeman 2004). Individuals derive utility, which is a measure of benefit or value, from the environment according to the unique preferences that each individual holds (Freeman 1999, Daily et al. 2000).

As shown in Figure 3.1, the total economic value (*TEV*) of an environmental good or resource is composed of two types of values: passive-use value (*PUV*) and use value (*UV*).

$$TEV = UV + PUV \tag{3.1}$$

Figure 3.1. Types of Economic Value



Passive-use value is the value of a resource that accrues to individuals without the need to actually visit a site or physically use a resource Individuals gain satisfaction from knowing the resource exists now and in the future. Passive use values can arise from multiple motivations including: knowledge that a particular environmental good exists, preservation of the good for future generations and from the option to utilize the good at some point in the future (Krutilla 1967). These are known as existence, bequest and option value, respectively, and all generate utility for individuals that have a positive willingness to pay for them (Carson et al. 1999). Because some passive use values, such as existence value can benefit people over large geographic scales, even worldwide, passive use values can be very large and have the potential to dwarf use values. Therefore, proper definition of the population impacted by an environmental change is very important when aggregating passive use values to avoid over or under-estimation of values.

Use value is the value that society gains from the direct or indirect use of a resource through activities such as hiking, biking, wildlife viewing and hunting. Use value of an environmental good or service is the maximum willingness of society to pay for the direct or indirect use of ecosystem services provided by the environmental good. The direct use of a resource can be either consumptive or non-consumptive. Consumptive use of resources, like timber harvest or hunting, uses up the resource and diminishes the potential for future use of the resource. Non-consumptive use of a resource, such as wildlife viewing and the provision of ecosystem services by a forest like protecting water quality or sequestering carbon, does not use up the resource. **3.1.2 Market Failure**

In the case of private goods that are bought and sold in markets, preferences are revealed through the interaction of supply and demand. Microeconomic theory tells us that, under the assumptions of perfect competition, the optimal price of a good is determined by the intersection of supply and demand, resulting in an efficient allocation of resources to the production of the good. The values generated by an environmental good often do not have market prices that reflect their social value as a result of market failure and lack of property rights (Hanley et al. 2007). Market failure often results in the under-allocation of resources to manage and conserve environmental goods. Among other sources, market failure can arise when a good exhibits the qualities of a public or common property good, or generates positive or negative externalities.

3.1.2.1 Public and Open-Access Goods

The properties of rivalry and excludability can intersect in different combinations to produce five different types of goods. The five types of goods are: private goods, club goods, pure public goods, open-access goods (Table 3.1.) and mixed goods (not included in Table 3.1). Public goods are non-rival and non-excludable in consumption. Open-access goods are rival but non-excludable in consumption. Club goods are excludable but non-rival in consumption. Private goods are both rival and excludable. Mixed goods are any goods that don’t fall neatly into the excludability and rivalry definitions of one of these four types of goods, and may exhibit characteristics of two or more types of goods.

As illustrated in Table 3.1, pure public goods exhibit both the qualities of non-excludability and non-rivalry. A good is non-excludable when access to it cannot be denied to anyone once it has been provided to someone. A common example of this is air quality from which everyone benefits regardless of who paid the costs to provide it. Because of their non-rivalrous characteristics, public goods are vulnerable to free riding. Free riding occurs when a consumer of a good conceals their positive WTP for a good and enjoys the benefits from the good without paying for it. The consumer has no incentive to pay for their consumption of the good because they cannot be excluded from consuming it once it has been provided.

A good is non-rivalrous when consumption of the good by an individual does not diminish the ability of another individual to consume the good. In other terms, the marginal social cost of supplying an additional unit of a non-rival good is zero (Hanley et al. 2007). An example of this is the ozone layer, from which any individual can enjoy the benefits of protection from harmful UV rays without diminishing the benefits for any other individual.

Table 3.1. Types of Goods

	Excludable	Non-Excludable
Rivalrous	Private e.g. food, clothing, cars	Open-Access e.g. fish stocks, public pastures
Non-Rivalrous	Club e.g. private parks or lakes	Pure Public e.g. ozone layer, climate change protection, biodiversity

Open-access goods are non-excludable and rivalrous; making them susceptible to a problem known as the *tragedy of the commons*. The tragedy of the commons[3] describes the overexploitation of an open-access resource because consumers have the incentive to consume more than they otherwise would in a race to capture benefits from the good before it is degraded or depleted. This differs from the issue of under-allocation of a public good because of the rivalrous nature open-access goods, which when combined with non-excludability, can lead to overexploitation.

3.1.2.2 Externalities

A well-defined system of property rights is essential for market systems to result in an efficient allocation of resources in society. A well-defined system of property rights must be comprehensive, exclusive, transferable, and secure (Hanley et al. 2007). This means that all resources must be owned by someone, either privately or collectively; all benefits and costs from a resource must accrue to the owner; owner of resources must be able to sell or trade with one another; and a system of enforcement must be in place to protect property rights. However, when property rights are not well-defined, market failure can occur in the form of externalities. An externality is a benefit or cost from an action or transaction that accrues to a party or parties that did not willingly participate in the transaction. These are known as positive or negative externalities, respectively. The producer of the externality does not receive either payment for the benefits generated for third parties – in the case of positive externalities, or provide compensation for the costs imposed on third parties – in the case of negative externalities. As a result, too little of the environmental good or too much of the environmental bad - that is the externality - is produced. A common example of an externality is air pollution. Polluters reap the benefits associated with the activity that creates the pollution, whether it is the owner of a power plant,

[3] While this is the term commonly used to describe the issue, it is a misnomer because numerous examples exist of common property resources being managed efficiently (Ostrom 1990). The issue could be more accurately described as the tragedy of open-access resources.

or an individual's use of their vehicle, without having to pay for the costs that are imposed by their actions on other members of society.

3.1.3 Consumer Preferences

Neoclassical economic theory outlines assumptions about the structure of preferences for an individual consumer that form the basis of choice theory. In the context of nonmarket valuation, these assumptions apply to preferences concerning both market and nonmarket economic goods. Three essential assumptions or axioms of consumer theory assure the consistency or rationality of consumer preferences. The three assumptions of consumer preferences are: 1) Completeness – meaning an individual can rank any two given bundles of goods, even if that means to be indifferent between multiple bundles; 2) Transitivity - if bundle of goods, X, is preferred to bundle Y and bundle Y is preferred to bundle Z, then bundle X is preferred to bundle Z; and 3) Continuity – if an individual prefers bundle X to bundle Y, then they must also prefer a bundle that is suitably close to X to Y.

If these three axioms hold, then an individual is assumed to be able to order or rank bundles of goods in terms of desirability. The ability to make choices in the ordering of the bundles of goods is the foundation which allows further explanation of consumer behavior. This ranking represents the desires of the individual for the goods (or the characteristics of the goods) only, and is not dependent on money or the cost of the different bundles of goods. Money does play an important role because consumers possess only a limited amount and must therefore make tradeoffs in regards to which goods they choose to consume, but this comes into play in utility maximization, not the ranking of goods or bundles of goods. The objective of a consumer is to maximize utility received through consumption of goods, while being subject to various constraints.

As outlined by Flores (2004): In the case of the nonmarket goods, the individual must maximize utility through spending their income (or wealth) *y* on market goods *X* while being subjected to some level of nonmarket goods *Q*.

$$\max_{X} U(X,Q) \quad (3.2)$$

Subject to the constraints:

$P * X <= y$

$Q=Q_0$

where:

$X = [x_1, x_2, \ldots, x_n]$ is a vector of *n* market goods

$Q = [q_1, q_2, \ldots, q_k]$ is a vector of *k* nonmarket goods

$P = [p_1, p_2, \ldots, p_n]$ is a vector of prices for the *n* market goods

U(X,Q) is the amount of utility derived from a bundle of market and nonmarket goods.

The optimal level of X therefore depends on y, P and Q:

$$x_i^* = xi(P,Q,y) \quad (3.3)$$

the vector of optimal demand is therefore:

$$X^* = X(P,Q,y) \quad (3.4)$$

Evaluated the optimal demands, the utility function yields the conditional indirect utility function, *v*:

$$U(X^*,Q) = v(P,Q,y) \quad (3.5)$$

The conditional indirect utility function assigns a single number to each bundle of goods. The indirect utility function is conditional because the level of utility assigned is *conditional* on which bundle (or alternative profile) is selected. This number is ordinal, allowing bundles to be ranked in order but not allowing conclusions about the relative degree of difference between values to be drawn. The linking of the utility function to random utility models allows the estimation of economic welfare measures.

3.1.4 Welfare Measures

Changes in the quality or quantity of an environmental good have impacts on the magnitude of the values generated by the good. Depending on the nature of the change in environmental quality, a change in value can be either an economic benefit or an economic cost. The benefit of a positive change in environmental quality arises from the fact that society would be willing to pay a certain amount to achieve the improvement. The total willingness to pay (WTP) can be used to quantify the economic value of an environmental good or ecosystem service.

Economic benefit of an environmental improvement is defined as the difference between the total amount that society would be willing to pay for it and the price that they actually do pay for it. This is known as net willingness to pay, or consumer surplus. The value of reduced environmental quality on the other hand is defined by the willingness to accept compensation (WTA) to allow the degradation of the good or service (Hanley et al. 2007). Rationally, an individual's willingness to accept payment to give up a good that the already possess should be the same as their willingness to pay to acquire an identical good that isn't already in their possession. However, due to psychological concepts of loss aversion and the endowment effect, people tend to systematically value what they already have more highly than what they could acquire (Kahneman et al. 1991). As a result, estimates of WTA can sometimes be larger than WTP for the same good, so attention must be paid to what the appropriate measure of value is for any particular good being valued. However, in most empirical uses of stated preference techniques, the difference between the two measures has been very small (Bateman et al. 2002).

There are multiple measures of welfare change. The proper measure to use for any particular application is dependent on the context of the environmental good in question, whether the change will be in the price of a good or the quantity of the good and whether the population of interest will be made better off or worse off by the change, as well as assumptions about who holds the initial property rights.

Compensating welfare measures account for the amount of income that an individual would have to give up after an environmental change to be returned to the same level of utility as before the change.

$$v(P^0, Q^0, y^0) = v(P^1, Q^1, y^1 - C) \quad (3.6)$$

Equivalent welfare is a measure of the additional income an individual would need at the status quo conditions to obtain the same utility as the would have after an environmental change.

$$v(P^0, Q^0, y^0 + E) = v(P^1, Q^1, y^1) \quad (3.7)$$

Compensating variation (CV) and Equivalent variation (EV) are used to measure the welfare impact of a change in price. CV represents the offsetting change in income that is necessary to return an individual to their original level of utility given a new price. EV is the offsetting change in income that is necessary to give an individual the same utility at the original price, as they would have at the new price.

Compensating surplus (CS) and Equivalent surplus (ES) represent the change in welfare resulting from a change in quantity of an environmental good. CS represents the offsetting change in income that is necessary to return an individual to their original level of utility given a new quantity. ES is the offsetting change in income that is necessary to give an individual the same utility at the original quantity, as they would have at the new quantity. Equivalent and compensating welfare measures can be used in benefit-cost analysis of policies or management actions that affect environmental goods and services. Benefit-cost analysis can be used to determine if society is made better or worse off by a particular policy, or if multiple policy options exist, to determine which policy provides the most benefit. If the benefits produced by a policy exceed the costs associated with it, net economic benefits are generated and society is made better off by the policy. If the costs exceed the benefits, the policy can be deemed to be socioeconomically inefficient. When comparing multiple options, the policy that provides the largest net benefits is the most efficient option.

3.2 Valuation Methods for Nonmarket Goods

Revealed preference methods utilize complementary relationships that exist between some nonmarket goods and the market goods that facilitate reaping of benefits from those nonmarket goods. For example, the travel cost method utilizes expenses incurred during travel to quantify the value of recreational opportunities. Other revealed preference techniques include hedonic markets and abatement cost measures. Because of the need for a complimentary market good to infer values from, revealed preference techniques can only be used to estimate the value of goods for which this complimentary relationship exists. Therefore these techniques cannot be used to estimate passive-use values, which do not exhibit this type of complementary relationship with any market good. These techniques are not utilized in this study and are therefore not reviewed in this paper because the understanding of them is not essential to the results. However, more information on them can be found in Garrod and Willis (1999) and Champ et al. (2003).

Stated preference methods use carefully designed questions or choice tasks to elicit preferences for nonmarket goods. Because they do not rely on the existence of complimentary market goods, stated preference methods can be used to estimate both use and passive-use values. The most common state preference methods are contingent valuation and attribute-based methods. Contingent valuation is described first and is followed by a discussion of choice modelling which is the valuation technique employed in this research.

3.2.1 Contingent Valuation

The contingent valuation method (CVM) is the oldest and most widely applied stated preference method. Its first use was by Davis (1964) in the context of recreational big game hunting in Maine. CVM asks respondents whether they would be willing to pay a certain amount for an environmental good or service *contingent* upon a change in quality or quantity of that good. Various questionnaire formats exist including: dichotomous or binary choice, payment card and open-ended questions (Boyle 2003).

Critics of CVM argue that because respondents are only asked hypothetically what their WTP for a certain environmental good or change in environmental quality is, that their response is only hypothetical as well. However, in a study of the value of goose hunting, Bishop and Heberlein (1979) found that estimates of WTP from a contingent valuation study compared favorably to estimates found using travel cost and actual cash transactions. Probably the most well-known example of the CVM comes from the Exxon Valdez oil spill in 1989 where economists used CVM to estimate the damages done by the oil spill. In response Exxon funded the publishing of a book that questioned the fundamental premise of contingent valuation (Hausman 1993). The National Oceanic and Atmospheric Administration (NOAA) then convened a blue ribbon panel to evaluate the credibility of CVM. The blue ribbon panel concluded that CVM is indeed a reliable method for producing estimates of environmental damages (Arrow et al. 1993).

In addition to hypothetical bias, there are several limitations associated with CVM that arise from reliance upon respondents' statements of intention, including strategic bias, yeah saying, framing and insensitivity to scope (Bennett and Blamey 2001). Strategic bias can arise if respondents deliberately misrepresent their preferences in an attempt to influence the results. Yeah-saying is when respondents *state* a higher WTP than they would *actually* be willing to pay out of a desire to look good. Framing and insensitivity to scope may bias estimated WTP through a lack of consideration for substitute goods and the extent of the change in the environmental good or service being valued, respectively.

3.2.2 Attribute-Based Methods and Choice Modeling

Attribute-based methods (ABM) originated in the field of marketing as a way to understand how consumers choose between products by decomposing the items into their component characteristics or attributes. Economists adapted the technique through the inclusion of a price attribute in the choice set, to allow preferences for the characteristic attributes of environmental goods to be expressed in terms of dollar values. When used in this way, the technique is known as choice modeling (CM) or choice experiments (CE). Throughout this dissertation, the term choice modelling is used.

In choice modeling, an environmental good is decomposed into a technically divisible set of attributes that characterize the good being valued. Individuals are presented with choice sets that consist of multiple versions of environmental good, represented by varying levels of quality across the attributes of which the environmental good is composed. These different versions of the environmental good represent different potential future states of the world. In addition to the characteristics of the environmental good, each state of the world has an associated monetary cost associated with it. Individuals are asked to select their preferred option from a set of potential alternative profiles of the good. Typically, one profile represents a status quo or “no change” option, and one or more alternative profiles represent departure from the status quo. None of the profiles are strictly preferable to the others on all counts because each contains a mixture of improved, degraded, and status quo levels. Individuals are therefore forced to make tradeoffs between different attributes, having to accept degradations in some attributes in order to achieve improvements in the ones they value most highly. This approach allows the relative strength of preferences for each attribute to be revealed.

Choice modeling offers an improvement in some of the areas in which CVM has been criticized. A significant advantage offered by choice modeling is the ability to estimate a multi-dimensional valuation surface which allows a richer description of preferences than is possible with methods like contingent valuation (Holmes and Adamowicz 2003). Choice modeling also presents respondents with a more realistic scenario than the dichotomous choice presented to respondents in contingent valuation. Selection of an alternative from a choice set most closely mimics the real-life situations that consumers face when purchasing market goods, where they select a particular product from a selection of multiple brands or varieties with unique characteristics.

3.3 Choice Modeling Methods

As outlined by Bennett and Blamey (2001), choice modelling studies are typically conducted using the following seven steps, which are described in detail in the following sub-section. The steps are:

1. Characterize the decision problem

2. Select Attributes and Their Levels

3. Develop the Questionnaire

4. Create an Experimental Design

5. Create a Sample Design and Collect Data

6. Estimate Econometric Models

7. Conduct Policy Analysis

3.3.1 Characterization of the Decision Problem

In order to clearly define the environmental and economic problem to be investigated, the scope of the change in environmental quality must be identified. This includes the geographic and temporal scope of the problem, as well as case-specific issues related to the scope of the environmental good. The types of values associated with the change in environmental quality must be identified. Will the change in quality affect use values, non-use values, or both? In order to determine what type of values will be affected, the researcher must identify who will be affected by the change in environmental quality and in what ways they will be affected.

Often the results of CM exercises are used as inputs for cost-benefit analysis, which rely on the value of marginal changes in the quality or quantity of environmental goods. In order for the results of a CM exercise to be compatible with this framework, the exercise must be conducted in a way that allows values to be estimated at the margin. To facilitate marginal analysis, the issue must be framed in terms of change from the status quo or base case situation (Bennett and Blamey 2001).

3.3.2 Attribute and Level Selection

After the decision problem has been defined, the relevant attributes must be identified and characterized. Attributes are the environmental or socioeconomic characteristics that are known or hypothesized to change as a result of the management action. They can also be thought of as the potential costs and benefits associated with the management action. Potential attributes can be identified and defined through review of the relevant literature, communication with experts, and focus group discussions with representatives from stakeholder groups. It is important that attribute definitions can be understood by respondents, and that they facilitate quantification of the attribute in a way that is sensible and which allows respondents to compare different outcomes.

During this stage of the design, the number of attributes and the levels across which they will vary must also be determined. The set of attributes must be narrowed from all potential impacts to a subset that is believed to be of most concern to the population of interest. Care should be taken to ensure that attributes are relevant to both respondents and policy makers (Bennett and Blamey 2001). Because the complexity of the choice task increases as the number of attributes increases, only the attributes deemed to be most essential to the problem should be included in the survey. As the complexity of the choice task increases, so does the cognitive burden placed on respondents. Respondents may react to increased cognitive burden by utilizing heuristics such as ignoring some or all of the attributes (attribute non-attendance) (Hensher 2006), or selecting the status quo at an increased rate to avoid making a decision or to retain the situation they know (Boxall et al. 2009). Although there is no strict rule defining how many attributes should be included in a choice experiment, five or six (including a cost attribute) is a common number of attributes to include (Holmes and Adamowicz 2003).

Once the set of attributes has been determined, the levels across which each attribute varies must be defined. Levels can be expressed either quantitatively or qualitatively and must represent believable scenarios. They must also span a range that is large enough to make the attribute relevant for the respondent's decision and reflect the potential future conditions that could occur. It is especially important that the upper bound of the cost attribute is sufficiently high that very few respondents would be willing to select it. Otherwise the WTP function fitted to the data may not be properly bounded and result in an over-estimation of WTP.

3.3.3 Questionnaire Development

Choice sets need to be imbedded within a larger document that provides instructions and background information, as well as accomplishing other essential tasks like framing the issue and collecting sociodemographic and attitudinal information. Questionnaires follow a fairly standard pattern, as described in the following sub-sections.

3.3.3.1 Introduction

Through a pre-survey notice letter and at the beginning of the survey document, respondents are introduced to the issue being investigated and convinced of the importance of the research. It is essential to convince respondents of the importance of the research being conducted and the importance of their response in order to encourage participation. This can be accomplished, in part, by stressing that the data collected in the survey will be used to inform policy and management decisions. In order to convince respondents of the legitimacy of the research and to allay fears of unscrupulous practices, the credentials of the researchers and the institutions with which they are associated must be provided.

3.3.3.2 Problem Statement and Potential Solution

Next, the issue under investigation must be introduced. This involves describing the current conditions, as well as potential improvement or worsening of those conditions in the future if status quo policy and management continues. After the issue under investigation has been described, a potential solution to the problem must be provided. This involves describing how the environmental good might change in the future and how policy and management changes could potentially address the problem. It should be explained that outcomes for some important attributes related to the issue could be improved, while others may be negatively affected by these changes.

The manner in which the potential solution would be funded must also be identified. This requires description of a payment vehicle, which is presented as the means through which the potential solution would be funded. The payment vehicle should be presented as a realistic mechanism and compulsory mechanism to limit hypothetical bias. Examples of payment vehicles include: the introduction or increase in a mandatory use fee, an increase in a tax, the introduction of a bond measure, or an increase in a bill paid for a related good.

The appropriate context for the issue must be framed in the respondents' minds to ensure that respondents do not place too much weight on the issue under investigation, and that they are reminded of substitute and complementary goods, as well as their budget constraint and other things which they may wish to spend their money on. Introductory questions which ask respondents to rank competing goods helps establish the appropriate frame, while also getting respondents used to making tradeoffs, which they will be asked to do more of in the choice sets. The appropriate frame should make respondents aware of competing uses for public funds and competing individual expenses and the respondents' budget constraint.

3.3.3.3 Definition of Attributes

Definitions of the attributes to be valued must be provided as part of the introduction of the choice sets to allow respondents to make informed decisions when completing the choice sets. Care must be taken to describe the attributes accurately and consistently in order to limit the number of assumptions that respondents make about them. In order to help respondents understand the choice sets, a section must be included prior to the actual choice sets which explains the layout of the choice sets, the strategy that should be used to select preferred alternatives and the nature of tradeoffs respondents will be asked to make. It can be helpful for an example choice set to be included in this section of the survey instrument.

3.3.3.4 The Choice Sets

A number of decisions must be made in regards to the design of the choice sets. Design decisions include: whether choice sets will be generic or labeled, how many alternatives will be included in each choice set, and how the choice sets will be presented visually. Labelled alternatives have descriptors that go beyond the levels of the attributes. Labels can be used if the type of policy action used to achieve environmental change varies between alternatives and is likely to affect the choices that respondents make. Alternatively, if the policy action does not vary between alternatives, or is unlikely to affect respondents' choices, generic labels such as "alternative A, B, or C" can be used.

When determining the number of alternatives to present in each choice set, the analyst must consider the ability of respondents to comprehend the volume of information in each choice set, their patience in answering multiple choice sets, and the number of alternatives needed in each choice set to allow statistical analysis of the tradeoffs presented. Choice sets contain a significant amount of information that must be processed by respondents in order to make their choices and care must be taken not to overwhelm respondents. If more information is presented than the respondent can deal with, the respondent may make random selections or rely on decision making shortcuts rather than considering the tradeoffs presented to them.

Finally, the researcher must decide how to present the choice sets visually. Should the alternatives be presented in rows or columns? Should images be used to identify the various attributes? These choices should be made with the goal of maximizing clarity for the respondents. It is important that respondents are provided with an option to not select one of the alternative profiles, just as a consumer would have the option not to purchase any item in an actual market. Equivalently, allowing respondents to select the status quo represents having a “choose not to choose” option.

3.3.3.5 Sociodemographic Data Collection

Following the choice sets, there is a section containing questions designed to provide the researcher with context in regards to motivations behind the selection of alternatives made by respondents in the choice sets. Certain response aberrations should be addressed in order to understand the motivations behind certain types of respondents. Respondents who always choose the status quo option may have true preferences for the status quo, but in some cases this behavior represents a protest response against the payment vehicle, rather than a true expression of preferences toward the good. Other types of responses that suggest that respondents did not express their true preferences include: Respondents who make choices based only on the level of one or few attributes, or always select the alternative with the lowest cost (lexicographic preferences); and respondents who agree to pay in order to experience the good feeling of supporting a cause, rather than because of a true value for the environmental good (perfect embedding).

Follow-up questions should also be used to identify problems that respondents faced in completing the survey, including their ability to understand the questions and information provided, and whether they perceived the questionnaire to be biased or the scenarios presented to be unrealistic (Bennett and Blamey 2001). Either near the beginning, or at the end of the survey, socioeconomic and demographic data should be collected to allow the researcher to check how well the sample obtained represents the general population of interest. Along with the levels of the attributes, this data is used as explanatory variables in the modeling of selection of alternatives made by respondents. If it is found that certain segments of the population are under or over-represented in the sample, weighting should be used in the aggregation of economic welfare measures. Information about general attitudes toward the environment and specific attitudes toward environmental issues related to the decision problem should also be collected. If specific characteristics are hypothesized to affect preferences for the environmental good being studied, information about these characteristics should be collected because they can be used to account for preference heterogeneity.

3.3.4 Experimental Design

The fitting of CM data to models relies on the differing probabilities of selection of an alternative that arise from the combinations of attribute levels available to choose from. In order to separate out the effect of each specific attribute on choice, many different combinations must be presented. The combination of attributes and attribute levels that are presented to respondents in the choice sets is known as the experimental design. Experimental design determines the type of effects that can be analyzed and the interpretation of those effects. Experimental design is also required to avoid biased parameter estimates and collinearity amongst variables.

Ideally, the entire array of potential combinations would be included in the study, but as explained in the following sub-sections, this is often not feasible. Therefore, methods such as fractional factorial design and blocking are often used to limit the number of combinations which are presented, while minimizing the amount of information that must be sacrificed.

3.3.4.1. Full Factorial Design

Full factorial design combines every level of each attribute with every level of all other attributes. The primary advantage of a full factorial design is that all main effects and interaction effects are independent or orthogonal and can be identified (Holmes and Adamowicz 2003). Main effects are the effect that a change in the level of a single attribute has on the probability of an alternative being selected. Interaction effects are the change in probability of an alternative being selected caused by simultaneous change in the levels of two or more attributes. Interaction effects occur if preferences for one attribute depend on the level of one or more other attributes. The main drawback to a full factorial design is that the number of combinations increases exponentially as the numbers of attributes and levels are increased. The total number of combinations depends on, the number of attributes (N), and the number of levels (L) for each attribute. The exact number of combinations is given by the equation L^N. So with three attributes that each vary across two levels, the total number of combinations is equal to 2^3 or 8. In the case of 5 attributes with 4 levels each, the total number of combinations is 4^5 or 1024 attribute-level combinations. Due to the exponential growth in the number of combinations as more attributes and levels are added, the number of possible combinations quickly becomes much too high to consider including all combinations in the survey. Fortunately, techniques such as fractional factorial design (Louviere et al. 2000) and blocking can be used to reduce the number of alternatives which must be presented to each respondent.

3.3.4.2 Fractional Factorial Design

Fractional factorial design can be used to maximize statistical efficiency and reliability of the information collected with choice modelling while limiting the number of choices that each respondent is asked to make (Johnson et al. 2007). Limiting the number of tasks presented to each respondent minimizes the cognitive burden placed on the respondent and reduces the amount of time they must invest in the survey (Holmes and Adamowicz 2003). Minimizing the time and effort required by respondents improves reliability of the information collected (Johnson et al. 2007). However a fractional factorial design comes with the cost of some lost information because it does not allow for the inclusion of interaction effects between attributes.

In economic analysis, interaction effects can be important because they capture possible substitution and complementary relationships between goods (attributes in this case). Fractional factorial design therefore requires that the assumption be made that utility is impacted only by main effects. If variables that explain variation in utility are omitted from the model, the estimated parameters may suffer from omitted variable bias. Fortunately, main effects tend to account for the majority of the explained variance in choice models. So, ignoring interaction effects is likely to be a reasonable trade-off to make unless there is an a priori reason to suspect that there are significant interaction effects that exist between the attributes (Louviere et al. 2000).

The potential impact of fractional factorial design on parameter estimation can be illustrated through the use of effects coding. With effects coding, the presence or absence of each attribute under main effects can be identified with a +1 for present or a -1 for absent. Table 3.2 gives the full factorial design matrix for an experiment with three attributes of two levels each. In the table, -1 represents absence of the attribute and +1 represents presence the attribute (with present and absent being the two possible levels). The A1*A2 interaction effect is given by a column produced by the multiplying the elements column A1 by the elements in column A2. The A1*A2 column is perfectly collinear through the first four profiles with the vector of values for A3. Therefore when using a fractional factorial design, which only includes independent vectors, the effect of A3 cannot be isolated from the effect of A1*A2 in the model.

Table 3.2. Full Factorial Design

	Main effects			2-way interaction effects		
Profile	A1	A2	A3	A1*A2	A1*A3	A2*A3
1	-1	-1	+1	+1	-1	-1
2	-1	+1	-1	-1	+1	-1
3	+1	-1	-1	-1	-1	+1
4	+1	+1	+1	+1	+1	+1
5	-1	-1	-1	+1	+1	+1
6	-1	+1	+1	-1	-1	+1
7	+1	-1	+1	-1	-1	-1
8	+1	+1	-1	+1	+1	-1

3.3.4.3 Blocking

To further reduce the number of alternatives presented to each respondent, choice sets can be assigned to independent subsets of the overall design, or blocks. Blocking can be done by considering blocks as an additional attribute in the experimental design, which has a number of levels equal to the number of desired blocks. This method ensures that every level of each attribute is present in every block.

3.3.5 Sample Size and Data Collection

The next step in the implementation of a choice modelling study is to decide what the sampling frame will be, how many surveys will be administered, and what the sampling strategy will be. The sampling frame defines the totality of respondents from which a finite sample of will be drawn and is determined by the objectives of the study. The size of the sample to be drawn depends on the size of the population being studied, the level of precision desired for the results and the available budget. Although there are no concrete rules for sample size, because sample error is a function of sample size, the more responses that are collected, the more likely it is that data analysis will produce results that are statistically significant and Louviere et al. (2000) suggest at least 50 respondents per block version.

The sampling strategy defines the manner in which the sample will be drawn from the sampling frame. Common strategies include a simple random sample and a stratified random sample (Louviere et al. 2000). In a simple random sample, each individual in the sample frame has a known and equal probability of selection in the sample. In a stratified random sample, the sample frame is divided in a number of mutually exclusive groups, from which simple random samples are individually drawn. Each individual within a group has the same probability of selection, but the proportion of samples drawn may vary between groups. Stratification can be used to correct for the fact that certain segments of the population will occur less frequently in a simple random sample, or to ensure that enough samples are drawn from segments of the population that are of particular interest to the study question.

Multiple modes of administration of a nonmarket valuation survey exist. Modes include: in-person, telephone, mail, internet-based, and mixed mode. Each mode has strengths and weakness, requiring tradeoffs to be made between survey administration costs, time constraints, sample coverage, and sample non-response bias (Champ 2003). In-person interviews tend to generate the highest response rates but are the most expensive to implement and are subject to potential interview bias. Telephone is typically the lowest cost method, but does not allow for presentation of visual aids (which can be problematic for choice modelling). Mail-out, mail-back methods are also relatively inexpensive compared to in-person interviews, but can suffer from low response rates and sampling bias as a result (Bennett and Blamey 2001). However, there are methods that can help improve response rates, and the four-contact method described by Dillman (2007) is a well-accepted way to maximize response rate. Using the four-contact method, respondents receive 1) a pre-survey notice letter, 2) the survey questionnaire, 3) a thank-you postcard, or a reminder post-card, 4) a replacement questionnaire. Internet survey modes are increasingly popular and can offer advantages over other survey modes in cost, speed of receiving responses, and ability to present information. Questions still exist however about the ability to collect a representative sample of the population with internet surveys. Mixed-mode surveys offer respondents multiple ways to respond. For example, respondents can be offered the option to respond via mail or internet, thus alleviating some concern about the ability to sample people who don't have access to the internet.

3.3.6 Model Estimation

After data collection is complete, preference parameters are estimated econometrically. The choice of which econometric model to use depends on a number of assumptions and considerations that are discussed in the Section 3.3.6.2. Regardless of which model specification is chosen, analysis of choice modeling data is based on economic theory, which is discussed in Section 3.3.6.1.

3.3.6.1 Theoretical Foundations **for Attribute-Based Methods**

Models used to analyze choice modelling data are based on a theoretical foundation that lies in two economic theories of consumer behavior: the characteristics theory of value and random utility maximization (RUM).The characteristics theory of value, developed by Lancaster (1966), states that consumer demand for a given commodity is determined by the commodity's characteristic attributes, as opposed to the traditional view that goods themselves are the direct object of utility. RUM explains utility as the sum of two components; one is systematic and the other is random. Individual choice behavior itself is assumed to be without error (i.e. non-random), but is manifested in a stochastic or random manner when researched, due to preference characteristics of individuals that are unobservable by the researcher (Holmes and Adamowicz 2003).

$$U_j = V(x_j, p_j;\ \beta) + \varepsilon_j \tag{3.8}$$

Where U_j is the true but unobservable utility associated with the consumption of profile *j*, *v* is the systematic indirect utility function, x_j is a vector of attributes associated with profile *j*, p_j is the cost of profile *j*, β is a vector of preference parameters and ε_j is a random error term. *V* is assumed to be homogeneous across the population, while the random error term is individual specific, reflecting individual idiosyncrasies of tastes.

The random utility model assumes that an individual will only select alternative *i* over alternative *j* if the utility associated with alternative *i* is greater than the utility from alternative *j* $U_i > U_j$. Equivalently, *i* is chosen if and only if the sum of systematic and stochastic components is greater for alternative *i* than for alternative *j*$(V_i + \varepsilon_i) > (V_j + \varepsilon_j)$.Rearranging yields grouped systematic components and grouped stochastic components $(V_i - V_j) > (\varepsilon_i - \varepsilon_j)$.

Because the stochastic components are unobservable, whether or not the above statement is true cannot be exactly determined. Instead, predictions must be made based on the probability that $(\varepsilon_i - \varepsilon_j)$ is less *than* $(V_i - V_j)$. The probability that an individual will choose alternative *i* from a choice set C can be represented by:

$$P(i \mid C) = P(U_i > U_j) = P(v_i + \varepsilon_i > v_j + \varepsilon_j), \forall j \in C \quad (3.9)$$

The preceding equation states that the probability of a randomly selected individual from the population of interest choosing alternative *i* over alternative *j*, is equal to the probability that the sum of systematic and stochastic elements of utility from alternative *i* are greater than the sum of systematic and stochastic elements of utility from alternative *j*. This can be rearranged to yield:

$$P(i \mid C) = P(U_i > U_j) = P(vi - vj > \varepsilon_i - \varepsilon_j), \forall j \in C \quad (3.10)$$

which states that the probability of choosing alternative i over alternative j, is equal to the probability that the difference between the random components of utility from alternatives i and j is less than the difference between the systematic components for those same alternatives.

3.3.6.2 Multinomial Logit Model and Variations

The selection of a model to analyze a choice modelling data set is sensitive to assumptions about the distribution of the random error term. If the errors are assumed to follow a type 1 extreme value distribution, also known as a Gumbel distribution, the multinomial logit (MNL) model (McFadden 1973) is most appropriate. The MNL is the most commonly used model in the econometric analysis of choice modelling data sets and it, along with variations, are used in this research. If errors are assumed to be normally distributed, a binary probit model can be used.

A number of assumptions must be made to make the MNL tractable. The first assumption is that choices made by respondents have independence from irrelevant alternatives (IIA), meaning that the selection of an alternative from a choice set is unaffected by the presence or absence of other alternatives in the choice set (Louviere et al. 2000). Second, errors are assumed to be independently and identically distributed (IID) (Hensher et al. 2005). A third key assumption that must be made is that preference structures are homogeneous across respondents (Holmes and Adamowicz 2003).

Assuming the errors in the regression can be described by a Gumbel distribution and are independently and identically distributed, the probability that an individual will select alternative *i* over alternative *j*, can be expressed as

$$P(i|C) = \frac{\exp(\mu V_i)}{\sum \exp(\mu V_{j)}} \tag{3.11}$$

where μ is a scale parameter inversely proportional to the variance of the error term. By assuming constant error variance, this parameter can be set to equal one (Ben-Akiva and Lerman 1985). This can be expanded and expressed as

$$P_n(i|C_n) = \frac{exp(\beta_{ni}X_{ni} + \alpha C_n + \tau Q_{ni})}{\sum exp(\beta_{nj}X_{nj}\ \alpha C_n + \tau Q_{nj})} \tag{3.12}$$

where X_{ni} is a vector of terms for the attribute levels encountered by individual n; β_{ni} is a vector of associated estimated coefficients; C_n is the cost attribute associated with each alternative and α is the associated coefficient; Q_{ni} is an alternative specific constant (ASC), taking a value of 1 for status quo alternatives and zero otherwise, with an associated coefficient of τ; and i and j are as previously defined.

For a sample size of N, and respondent choice represented as yin = 1 for an alternative that is selected and yin=0 for alternatives that are not chosen, a likelihood function can be written as,

$$L = \prod_{N=1}^{N} \prod_{i \in C} p_n(i)^{y_{in}} \tag{3.13}$$

Substituting the probability of selecting alternative i into the likelihood function and taking the natural logarithm yields the log likelihood function:

$$lnL = \sum_{n=1}^{N} \sum_{i \in C} y_{in} \; (\sum_{k=1}^{1} \beta_k x_{ikn} + \; \beta_p \, p_{in} - ln \sum_{k=1} (\sum_{k=1}^{1} \beta_k x_{jkn} + \; \beta_p p_{jn}) \tag{3.14}$$

Using maximum likelihood estimation (MLE), β values that maximize the log likelihood function are estimated. MLE is based on the concept that a given sample could be generated by multiple different populations but is more likely to come from one particular population. Population parameters such as mean and variance are chosen to maximize the likelihood of generating the observed sample repeatedly (Louviere et al. 2000).

The assumption of preference homogeneity can be problematic if preferences vary systematically as a result of characteristics that are not accounted for in the model. In the model represented by equation (13), preferences are assumed to be homogeneous across respondents, which may not hold true because there are individual characteristics that are likely to explain some portion of the preferences that people have toward environmental goods. This assumption can be relaxed through the inclusion of individual-specific characteristics as interaction terms with the attribute levels.

$$P_n(i|C_n) = \frac{exp(\beta_{ni}X_{ni} + \lambda_{ni}X^2{}_{ni} + \alpha C_n + \tau Q_{ni} + \gamma R_n X_i + \theta R_n C_n)}{\sum exp(\beta_{nj}X_{nj} + \lambda_{nj}X^2{}_{nj} + \alpha C_n + \tau Q_{nj} + \gamma R_{nj} + \theta R_n C_n)} \tag{3.15}$$

R_n is a vector of case-specific socioeconomic characteristics that is interacted with the alternative-specific attribute-level variables, and has an associated coefficient of γ; and i and j are as previously defined.

Variations on the basic MNL allow some of the assumptions that are required for the basic version to be relaxed, allowing more flexibility in analysis. Variations of the basic MNL include the nested logit model, the random parameters logit model, and the latent class model. The nested logit model allows the IIA assumption to be relaxed by decomposing utility into a multi-stage decision, with the utility associated with a particular outcome being conditional upon a previous tier of decision making that determines the outcomes that are possible. This approach is especially useful for recreation studies, where preferences are determined first by the decision of whether or not to participate, and then on the quality of the recreation, conditional on choosing to participate. Both the latent class and random parameters models can be used to address preference heterogeneity. The random parameter logit approach assumes that preference parameters are randomly distributed throughout the population and accounts for it through the estimation of the mean and variance of the random parameter distribution (Train 1998). The latent class model provides the ability to identify subsets of the population with similarities in preference structures. The latent class and random parameter approaches each have benefits and the choice of which to use to address preference heterogeneity depends in part on assumptions about the nature of the heterogeneity that needs to be accounted for. The latent class model was chosen for this research because of its ability to describe distinct groups of preferences within the population. A detailed description of the latent class model follows.

3.3.6.3 Latent Class

The LC framework assumes that individuals are members of a group that has certain preferences, independent from the choice problem being analyzed (Swait 1994). Preferences differ across groups, but are homogeneous within groups. Given *S* classes in the population and individual *n* belonging to class $s(s = 1,\dots,S)$, the indirect utility function can be written as:

$$U_{in|s} = \beta_s X_{in} + \varepsilon_{in|s} \tag{3.16}$$

where β_s is the vector of preference parameters for class *s*, X_{in} is a vector of individual and alternative specific characteristics and $\varepsilon_{in|s}$ represents the random component of utility for individual *n* of class *s*. The probability of selecting alternative *i* is now partially dependent on what class of the population the respondent belongs to, with preference parameters varying by class:

$$P_{n|s}(i) = \frac{exp(\beta_s X_i)}{\sum_{k\in C} exp(\beta_s X_k)} \tag{3.17}$$

However, before this probability can be estimated, individuals must be sorted into their respective segments. Inclusion in a particular class is defined by some socioeconomic, demographic and attitudinal characteristics hypothesized to affect preferences. Assuming we know the number of latent segments in the population, there is an unobservable latent membership likelihood function Y^*_{ns} that classifies individuals into different segments (Swait 1994).

$$Y^*_{ns} = \Gamma_{ps} G^*_{np} + \Gamma_{as} G^*_{na} + \Gamma_{zn} X^*_{nz} + \zeta_{ns} \tag{3.18a}$$

$$X_{np} = B_p G^*_{np} + \zeta_{np} \tag{3.18b}$$

$$X_{na} = B_a G^*_{na} + \zeta_{na} \tag{3.18c}$$

Y^*_{ns} is a function of general attitudes as well as sociodemographic characteristics for individual n and segment s. X_{np} *and* X_{na} are vectors of observed individual attitudinal indicators. G^*_{np} is a vector of individual general latent perceptions. X^*_{nz} is a vector of observed sociodemographic characteristics. Γ_{ps}, Γ_{as}, Γ_{zn}, B_p, B_a are parameter vectors to be estimated and ζ_{ns}, ζ_{np}, ζ_{na} are error terms. As outlined by Holmes and Adamowicz (2003), identification of class membership is accomplished through the following logit model:

$$P_{ns} = \frac{exp\ (\lambda_s Z_n)}{\sum_{s=1}^{S} exp(\lambda_s Z_n)} \tag{3.19}$$

Where *Z* is a set of individual characteristics and λ is a vector of parameters. Selection of the number of classes can be informed the Bayesian information criterion (BIC) and Akaike information criterion (AIC) (Swait 1994). In addition, *a priori* assumptions about the underlying elements of the heterogeneity and the practical explanatory interpretation of the classes can be taken into account.

The joint probability of individual *n* belonging to class *s* and selecting alternative *i* can also be defined as the expected value of the product of the probabilities defined in equations (3.19) and (3.20),

$$P_n(i) = \sum_{s=1}^{S} \left[P_{n|s}(i) P_{ns}\right] = \sum_{s=1}^{S} \left(\frac{\exp(\lambda_s Z_n)}{\sum_{s=1} \exp(\lambda_s Z_n)}\right) * \prod_{k=1}^{K} \left(\frac{\exp(X_{ink}\beta_s)}{\sum_{j=n} \exp(X_{ink}\beta_s)}\right) \tag{3.22}$$

where k = 1,…K are the choice sets presented to individual *i*.

3.3.7 Policy Analysis and Estimation of Welfare Measures

The final step in the conducting a choice experiment is to convert the parameter estimates obtained from the model into metrics that will serve to inform policy makers. Metrics can be both monetary and non-monetary. Monetary estimates based on WTP and WTA can be used to calculate economic surplus and changes in social welfare associated with marginal changes in the different attributes. Marginal Rate of Substitution (MRS) is a non-monetary measure which describes the tradeoffs that people are willing to make between the levels of the different attributes.

Differentiation of the utility function yields parameter estimates, which are interpretable as marginal utilities of each of the attributes. For attribute k:

$$\beta_k = {}^{\partial U}/_{\partial x_k} \tag{3.23}$$

The marginal rate of substitution (MRS) between any two attributes can be calculated as the ratio of two parameter estimates.

$$MRS_{km} = {}^{\beta_k}/_{\beta_m} \tag{3.24}$$

The marginal value (MV) or implicit price of an attribute is the ratio of the attributes parameter estimate and the parameter estimate on profile cost. Additionally the parameter on profile cost has another interpretation, because an increase in profile cost is the same as a decrease in income, its negative is interpretable as the marginal utility of money.

$$MV_k = {}^{\beta_k}/_{\alpha} = {}^{\partial U/\partial x_k}/_{\partial U/\partial C_j} \tag{3.25}$$

In this case, the *MV* that is calculated is in terms of *WTP*. In other words, MV_k is the average WTP per person or household for a marginal increase attribute *k*. For the LC model, WTP estimates are class specific:

$$MV_k = {}^{\beta_{sk}}/_{\alpha_s} \tag{3.26}$$

3.3.7.1 Aggregation of Welfare Measures

Welfare measures are derived from the model in the terms of per-person or per-household values. In order to assess total costs or benefits associated with any one of the attributes, these measures must be aggregated up to the population of interest (*N*); where N is either number of households or total population.

$$Aggregate\ MV_k = MV_k * N \tag{3.27}$$

Or

$$Aggregate\ WTP = WTP * N \tag{3.28}$$

However, this aggregation of WTP is only valid if the population of interest is known, a random sample has been drawn where each member of the population has a known and positive (though not equal) probability of being selected (Bateman et al. 2002). If these conditions have not been met, some segments of the population may be over or under represented. If different segments have an unequal probability of inclusion in the sample, WTP can be weighted by their probability of selection.

$$Aggregate\ WTP = N * \sum_{i=1}^{J} w_i\, WTP \tag{3.29}$$

Where w_i is the analytical weight for each individual *i*, and which sum to one (Bateman et al. 2002).

3.3.7.2 Statistical Accuracy of Welfare Measures

Like the estimated coefficients used in the estimation of MWTP, MWTP itself is a random variable. Therefore, measures of statistical uncertainty like standard error and confidence intervals should be estimated in order to assess the accuracy of MWTP estimates. Confidence intervals can be used to assess whether or not an estimate of MWTP is statistically different from zero – if the confidence interval does not overlap with zero, there is evidence that the estimate is statistically significant at the level at which the interval was set.

Two approaches to estimating confidence intervals for MWTP are bootstrapping and the delta method. As outlined by Efron and Tibshirani (1986), bootstrapping is a nonparametric method that can be used to obtain confidence intervals associated with MWTP estimates, without requiring that assumptions be made about the distribution of the coefficients. Using bootstrapping, a simulated distribution of MWTP values is generated by repeatedly drawing sample from the dataset and estimating MWTP using the model results produced by each sample. Percentiles obtained from the simulated distribution can then be used to calculate confidence intervals representing the desired level of confidence. As described by Hole (2007), the delta method relies on the assumption that MWTP is approximately normally distributed around its mean. In the delta method, the variance around the mean value of MWTP is calculated by taking the first-order Taylor expansion around the mean. The variance can then be used to construct a confidence interval around mean MWTP.

3.4 Summary of General Methods

Chapter 3 described why, as a result of market failures, markets sometimes fail to produce socioeconomically efficient outcomes for environmental goods and services. In these situations, nonmarket valuation techniques can be used to quantify the values that society has for these goods and services. These economic welfare measures can be used to evaluate and compare alternative policies when they are incorporated into benefit-cost analysis. Chapter 4 describes an application of these nonmarket valuation techniques in a case study that quantified willingness to pay for woody biomass energy generation and environmental effects associated with it.

3.5 Chapter 3 References

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Chapter 4

Case Study: Choice Modelling Survey of Woody Biomass Energy Preferences in the Rocky Mountain West

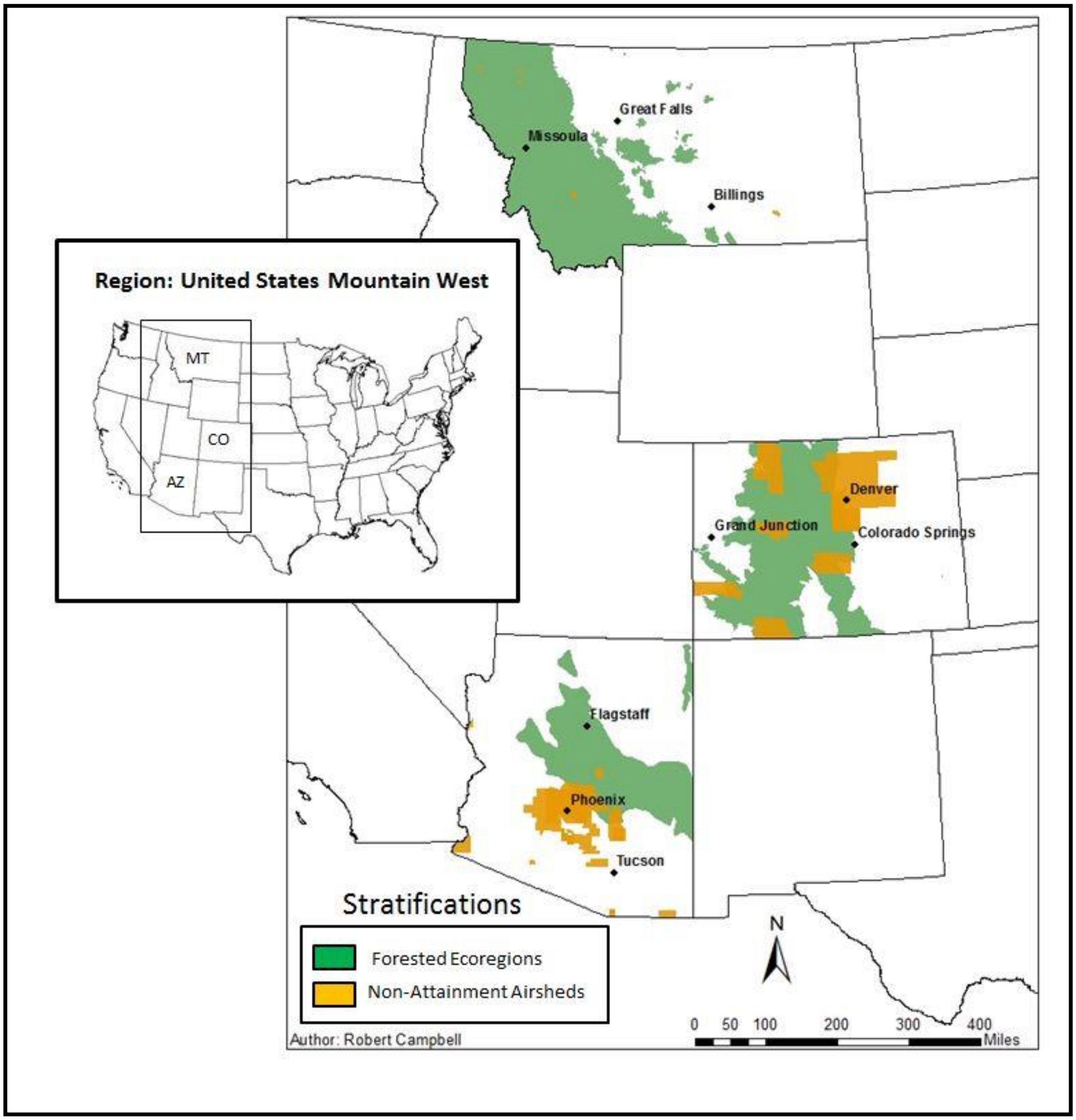
In Chapter 4, the case study that was conducted is presented. First, the rationale for the selection of the study area is explained, and sociodemographic, economic, and geographic characteristics that are pertinent to the study are described. Then, the development of the choice modeling survey is described. This includes selecting and defining the attributes and their levels, constructing the choice sets, and designing the survey instrument. The sample design and data collection methods are described next. Finally, summary statistics of the sample collected with the survey are presented and potential issues with the data that were explored and addressed are described. Results from econometric modeling and policy analysis are reserved for Chapters 5, 6, and 7.

4.1 Description of the Study Area

Montana, Colorado, and Arizona were selected as study states to represent the larger Mountain West or Rockies region of the US West of which they are a part (shown in Figure 4.1). The Mountain West is generally considered to consist of Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, and Wyoming. The three study states provide coverage of the large north-south geographic span of the region. The Mountain West is an important area in which to woody biomass energy because there are substantial amounts of woody biomass that could be used to produce energy. The majority of this biomass is on public lands, which provide numerous values to the public and are managed to facilitate multiple uses. Because it is likely that utilizing the biomass for energy will positively or negatively impact other values provided by public forests, it is important that the associated effects are quantified and incorporated into decision making about public land management. No past studies have analyzed public preferences toward woody biomass energy in the Mountain West or from public lands specifically. Although woody biomass energy is a relevant topic of study in many areas of the US, there are significant differences in land ownership and forest industry organization that make it impractical to conduct a study on public preferences that spans multiple regions because of the different context within which woody biomass energy exists in the different regions of the US.

Montana, Colorado and Arizona share some geographic and ecological characteristics that make the topic of woody biomass energy generation relevant in each state. However, each state has distinct geographic, economic, and sociodemographic characteristics which affect the environmental and socioeconomic outcomes associated with woody biomass energy generation. This section describes land ownership patterns in the region, sociodemographic characteristics, economy, energy resources and policies, and forest resources and industry in each state.

Figure 4.1. Study Area Map: The United States Mountain West



4.1.1 Public Lands and Forest Land

With almost half of the total area of the Mountain West under federal ownership, public lands are a significant part of the geographic and political landscape (Table 4.1). Of the three study states, Arizona has the largest proportion of federally-owned land, with 42.3% of land under the jurisdiction of the

United States Forests Service (USFS), National Park Service (NPS), Fish and Wildlife Service (FWS), Bureau of Land Management (BLM), or Department of Defense (DOD) (Gorte et al .2012). In Colorado and Montana, 36.2% and 28.9% of land is federally owned, respectively (Gorte et al .2012). When state lands are taken into account, the total amount of public lands in the study area is greater than 50%. There is a diverse array of ecosystem types across the study area, but forested ecosystems represent a significant portion of the landscape. At least one-quarter of the land in each state is forested, with Colorado containing the largest proportion of forest at 32.2% (Rummer et al. 2005).

Table 4.1. Geographic Characteristics of the Study Area

Characteristic	Arizona	Colorado	Montana	Mountain West
Land area (millions of acres) [a]	72.7	66.5	93.3	548.5
Federal land (millions of acres) [a]	30.7	24.1	26.9	292.7
Forest land (millions of acres) [b]	19.4	21.41	23.3	139.3
Percent of federal land in the state [a]	42.3	36.2	28.9	48.0
Percent of the state that is forested [b]	26.7	32.2	25.0	25.4

Sources: a. Gorte et al. (2012).
b. Rummer et al. (2005).

4.1.2 Socioeconomic Overview of the Study Area

Differences in the study states exist across key sociodemographic and economic characteristics like population size and density, income levels of residents, and size and composition of state GDP. Unless otherwise cited, values provided in this section can found in Table 4.2. Montana has less than 1 million residents, which when combined with its large area, make it one of the least densely populated states in the US. The state has a large rural population, with 44.1% of residents residing in rural areas. The largest urban area in Montana, Billings (population 114,773), is only a fraction the size of the largest cities in Arizona (Phoenix, population 3.6 million) and Colorado (Denver, population 2.4 million) (Census Bureau 2010a). Native Americans comprise the largest minority group in Montana, representing 6.5% of the state population. Hispanics, which comprise significant portions of the population in both Colorado and Arizona, represent only 2.9% of the population in Montana. Median household income in Montana in 2013 was $46,230, which is 9th lowest amongst all states (Census Bureau 2010a). Montana's GDP in 2014 was $44 billion, only about 1/6th the size of Arizona's and 1/7th the size of Colorado's. Natural Resources and Mining (including agriculture, forestry, fishing and hunting) is the largest industry in Montana, comprising 9.7% of GDP, while Tourism is the second largest industry (EIA 2015a).

Table 4.2. Sociodemographic and Economic Characteristics of the Study Area

	Arizona	Colorado	Montana
Population (2013) [a]	6.7 million	5.3 million	1 million
Percent Rural Population (2013)[a]	10.2	13.9	44.1
Percent Hispanic Population (2013)[a]	29.6	20.7	2.9
Percent Native American Population (2013)[a]	5.3	1.6	6.5
Median Household Income (2013)[a]	$49,774	$58,433	$46,230
Gross Domestic Product (2014)[b]	$284.2 billion	$306.6 billion	$44.3 billion

Note [a] source: Census Bureau (2014)
Note [b] source: BEA (2015)

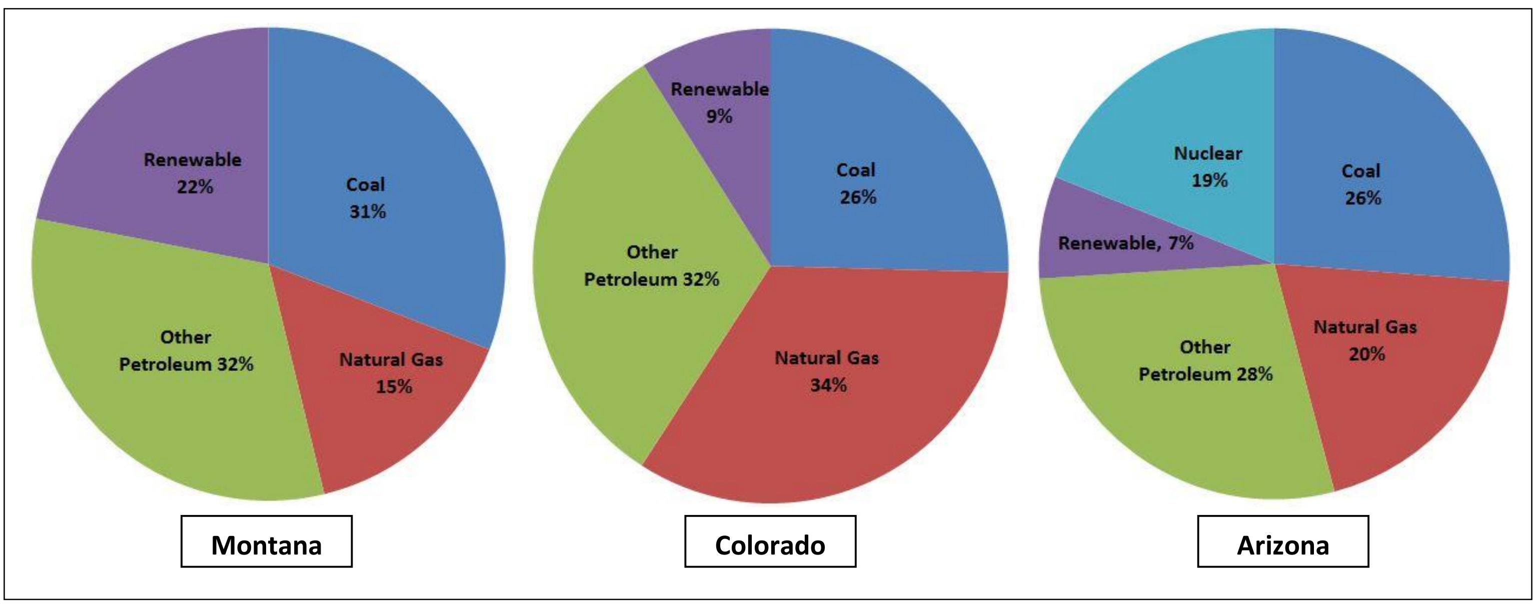
Arizona is the most populous state in the Mountain West, with a population of 6.4 million. Arizona has a much smaller proportion of rural residents than Montana. However, with 70% of the state's population concentrated in the Phoenix-Mesa and Tuscan urban areas, much of the state remains sparsely populated (Census Bureau 2010a). Arizona has a large Hispanic population, which accounts for nearly 30% of the state's population. Arizona has a median household income of $49,774 and a GDP of $284 billion, both of which are higher than Montana and lower than Colorado. Major industries include manufacturing and aerospace and defense (EIA 2015b). Natural resources and mining represent 2.9% of GDP, with Arizona producing more copper than any other state (BEA 2015).

Colorado has a population of 5 million; 13.9% of which are rural residents. Similar to Arizona, the majority of the population is concentrated in a few large urban areas, leaving much of the state sparsely populated. The largest minority group in Colorado is Hispanics, which comprise almost 21% of the state population. Median household income in Colorado is $58,433, highest amongst the study states. Colorado has a large and diversified economy, with a GDP of $307 billion and major industries that include aerospace and defense, research and sciences, and tourism (EIA 2015c). Natural resources and mining are also a significant part of the economy, constituting 7.3% of GDP.

4.1.3 Energy Mix in the Study Area

Energy characteristics vary across the study states. The states have a diverse range of energy resources and, consistent with their diverse economic and geographic characteristics, have diverse energy needs. The states also have diverse portfolios of energy resources. As seen in Figure 4.2, all three states currently rely heavily on those fossil fuels for energy consumption. However, all three states also contain significant renewable energy resources and have policies in place that encourage increased renewable energy generation and decreased reliance on fossil fuels in the future.

Figure 4.2 State Energy Consumption by Source, 2013



Notes: “Other Petroleum” includes motor gasoline, diesel fuel, fuel oil, jet fuel, and liquefied natural gas.
Sources: EIA (2015a), EIA (2015b), EIA (2015c).

Per capita energy consumption in Montana is higher than average, ranking 15th amongst all states (EIA 2015a). The industrial and transportation sectors in Montana are the highest energy consumers, which is consistent with the state’s sparse and dispersed population and economic reliance on agriculture and natural resources. Fossil fuels provide 77% of energy consumption in the state; the largest single source is coal, which accounts for 31% of energy consumption in the state (EIA 2015a). Montana has significant energy resources and is a net exporter of energy. The state holds over one-fourth of the recoverable coal reserves in the US, has substantial hydroelectric energy resources, and significant potential for expanded wind energy production (EIA 2015a). The state has a high proportion of renewable energy consumption, with 22% of energy provided by renewable sources (EIA 2015a). The largest source of renewable energy is hydroelectricity, which provides 78% of the renewable energy in the state (EIA 2015a).

Arizona ranks 44th out of the 50 states in per capita energy consumption (EIA 2015b). Energy consumption in Arizona comes from 77% fossil fuels, 19% nuclear power, and 7% renewable sources (EIA 2015b). Unlike Montana and Colorado, the industrial sector consumes the smallest amount of energy of any sector. Transportation and residential sectors consume the most energy, with air-conditioning accounting for 25% of all the energy consumed in the state (EIA 2015b). Coal is the largest single source of fossil fuel energy in the state, and the only fossil fuel of which Arizona contains significant reserves (EIA 2015b). Arizona is home to the largest nuclear power plant in the US and is a net exporter of energy to other states (EIA 2015b). The largest source of renewable electricity generation in Arizona is hydroelectric power produced by the Glen Canyon and Hoover Dams (EIA 2015b). However, Arizona's most significant renewable energy potential is from solar . The state has the largest solar photovoltaic facility in the world and has among the largest solar resources of any state (EIA 2015b).

Colorado's per capita energy consumption is below the national average, with the industrial sector accounting for the largest portion of energy usage (EIA 2015c). Amongst the three study states, Colorado's energy consumption relies the most heavily on fossil fuels, with 91% of state energy consumption provided by fossil fuels (EIA 2015c). Colorado has substantial fossil fuel and renewable energy resources, but is currently a net importer of energy from other states (EIA 2015c). The state has significant reserves of coal, oil, and natural gas Natural gas provides the largest share of energy consumption in the state, at 34% (EIA 2015c). The largest source of renewable electricity generation in Colorado is wind power, which accounts for 6.8% of electricity generation in the state (EIA 2015c). Hydroelectricity, produced mostly by small-scale facilities, provides the next-most renewable electricity (EIA 2015c). The state has significant potential for further expansion of wind power, as well as potential for solar energy development.

4.1.3.1 Relevant Governance and Public Policy

In addition to national level programs that encourage renewable energy production through subsidized loans, and production credits, all three of the study states have introduced renewable energy portfolio standards aimed at increasing the amount of energy supplied by renewable sources in the state (DOE 2015). Eligible renewable energy sources vary by state, but biomass is an eligible source in all three states (DOE 2015).

Montana's Renewable Portfolio Standard requires public utilities and competitive electricity suppliers serving 50 or more customers to obtain a percentage of retail electricity sales from eligible renewable sources (DOE 2015). As of 2015, the compliance rate is 15% of retail electricity sales from renewable sources (DOE 2015).

Arizona's Renewable Energy Standard requires investor-owned utilities and electric power companies serving retail customers in Arizona to obtain 5% of their retail electric load from eligible renewable sources as of 2015, and increasing by 1% per year to 15% by 2025 (DOE 2015). Additionally, 30% of the required renewable energy must come from distributed sources, half from residential sources and half from other non-residential, non-utility sources (DOE 2015).

Colorado's Renewable Energy Requirement Initiative requires that qualifying retail utilities must obtain a certain percentage of their electricity from renewable sources (DOE 2015). Investor-owned utilities must obtain 20% as of 2015 and 30% by 2020 from renewable sources; electric cooperatives serving more than 100,000 customers must obtain 6% as of 2015 and 20% by 2020 from renewable sources; electricity distribution cooperatives serving between 40,000 and 100,000 customers must obtain 6% as of 2015 and 10% by 2020 from renewable sources (DOE 2015).

4.1.4 Forest Resources and Industry

Table 4.3. Forest Resources and Industry, by State

Item	Arizona [a]	Colorado [a]	Montana [b]
Non-reserved timberland	3.4 million acres	11.4 million acres	19.9 million acres
Sawtimber volume [c]	29,800 MMBF	85,800 MMBF	124,200 MMBF
Timber harvest	53.8 MMBF	86.5 MMBF	374 MMBF
Number of sawmills	8	30	41
Production capacity [c]	78 MMBF	206 MMBF	611 MMBF
Primary wood product sales	$36.5 million	$101 million	$529 million

Note: a: Data source: Hayes et al. (2012). Data for year 2007.
b: Data source: McIver et al. (2013). Data for year 2009.
c: Note: MMBF = Millions of Board Feet Scribner

Not all forestland is classified as timberland. The US Forest Service definition of timberland is forest land that is producing or is capable of producing crops of industrial wood and not withdrawn from timber utilization by statute or administrative regulation, such as wilderness designation. Areas classified as timberland are capable of producing in excess of 20 cubic feet per acre per year of industrial wood in natural stands. With the most timberland and standing timber volume, Montana has the largest amount of timber resources of the three study states (Table 4.3). Montana also has the largest timber industry, with the most harvest, production capacity, and lumber output. Colorado has the second most timber resources and production. Arizona has the least amount of timber resources and smallest production capacity, with significantly less than Colorado and Montana.

A significant amount of timber harvesting in each of the study states takes place on public lands. In Montana 43.5% of timber harvest came from public forests (McIver et al. 2013). The 56.5% of timber harvest that came from private forests came from industrial ownership (27%), non-industrial private forests (NIPF) (25.6%) and tribal forests (3.9%) (McIver et al. 2013). In Colorado 52.2% percent of timber came from public forests, and the remainder came from tribal forest and NIPF (Hayes et al. 2013). In Arizona, 60.8% of timber came from private or tribal forests and 39.2% came from National Forests (Hayes et al. 2013). There is no industrial forest ownership in either Colorado or Arizona.

Timber harvest and lumber production has decreased from historic highs in the past decades in all three states. In Montana, timber harvest has declined from over 1,200 MMBF in 1988 (McIver et al. 2012). Timber harvest in Colorado declined from 103.4 MMBF in 1982 (Hayes et al. 2013). In Arizona, 382.7 MMBF was harvested in 1998 (Hayes et al. 2013).

4.1.5 Biomass from Forest Restoration Treatments

As a result of altered natural fire regimes, there are 67 million acres of forestland in the Western US that are either moderately or severely departed from historic conditions and could benefit from either prescribed fire, mechanized thinning treatments, or both (Rummer et al. 2005). Of these, over 28 million acres are severely departed from historic conditions and would require mechanized treatment before prescribed fire can be considered as a treatment option. Treatment of these acres represents a significant potential source of woody biomass feedstock. Mechanized thinning of all 28 million acres would produce 576 million dry tons of biomass, or about 20.5 dry tons per acre. Of this, 30% can be assumed to be in the form of residues (Perlack and Stokes 2011), equal to about 6 dry tons of residues per acre. Residues are defined as materials which are not suitable for use as traditional forest products, such as tops, branches, slash, cull, snags, coarse woody debris, and bark (Berger et al. 2013)

Out of the three study states, Montana has the largest potential supply of residues from mechanized thinning treatments. In Montana, there are 9.5 million acres of timberland in need of treatment, across all ownership types (Rummer et al. 2005). It is estimated that out of the 9.5 million total acres in need of treatment, 5.8 million acres are moderately departed from reference conditions and could be treated with prescribed fire alone, while the remaining 3.7 million acres are severely departed and would require mechanized treatment before prescribed fire can be considered as a treatment option (Rummer et al. 2005). The mechanized treatment of all 9.5 million acres could result in the removal of 56 million dry tons of residues, while mechanized thinning only the severely departed acres could result in the removal of 23 million dry tons of residues (Rummer et al. 2005).

In Colorado, there are 6 million acres of timberland that are moderately or severely departed from historic conditions. 3.5 million acres are moderately departed and the remaining 2.5 million acres are severely departed (Rummer et al. 2005). Thinning treatment on all 6 million acres could result in the removal of 30 million dry tons of residues, while thinning only the severely departed acres could result in the removal of 15 million dry tons of biomass (Rummer et al. 2005).

Arizona has the smallest number (but highest proportion) of acres in need of treatment, with 1 million acres of moderately departed timberland and 1.9 million severely departed acres (Rummer et al. 2005). Mechanized treatment of all 2.9 million departed acres would produce 17 million dry tons of residues, and treatment of only the severely departed acres would produce 12 million dry tons of residues (Rummer et al. 2005).

4.2 Development of the Choice Modeling Survey

Elicitation of public preferences toward woody biomass energy was undertaken using a choice modeling survey. The choice modeling method is dependent on obtaining responses to choice tasks that ask people to choose their preferred state of the world, as defined by varying levels of the attributes that comprise an environmental good. Implementation of the choice modeling survey required the undertaking of a number of steps. Attributes were identified and defined through collaboration with stakeholders and experts at focus group meetings. Metrics to quantify changes in the attributes were established and status quo levels were determined through state-level data collection. An experimental design was developed to allow the desired relationships to be analyzed with the eventual data set. A stratified sampling plan was developed to ensure coverage of the population of the study states. A survey instrument was developed, within which the choice sets were integrated, and additional information about the respondents was collected. The survey instrument was delivered to the sample population through three alternative survey modes. These procedures are described in detail in the following sections.

4.2.1 Focus Groups

In order to identify potential attributes to characterize the decision problem, focus groups were held in Missoula, MT, Denver, CO, and Flagstaff, AZ in July, August, and September 2013, respectively. Focus groups were attended by a diverse group of experts and stakeholders including representatives from state and federal public land management agencies, state environmental quality departments, private timber industry, non-profit wildlife and recreation groups, land trust groups, and academic researchers. Potential participants were identified via internet searches for organizations and agencies with an interest in the topic. Groups were contacted via email and phone and an interested representative was invited to attend the focus groups. Additional contacts were discovered through snowball sampling, which involves asking established contacts to suggest other potential participants. The goal was to have the most diverse set of viewpoints possible at the workshops, including participants representing organizations that are opposed to woody biomass energy. However, in the end, no representatives from groups with a clear anti-woody biomass energy stance were willing to participate in the workshops. For a full list of participants, see Appendix A.

Each workshop was attended by between 7 and 12 participants. Workshops began with an overview of the research project, including a description of the issue under investigation and a brief introduction to the choice modeling method. Next, a participant-led brainstorming discussion took place, during which participants were asked to identify all issues of concern, whether positive or negative, that they associate with the issue of woody biomass energy generation. During these discussions, the issues raised by participants were transcribed and mapped using XMind brainstorming software. The “mind maps” produced at each meeting are recorded in Appendix A.

After the potential attributes were identified, participants voted on the top 5 issues they believed to be of most concern to the public. These selections were used to generate a ranking of the attributes of most concern at each workshop by summing the number of votes received for each potential attribute (Table 4.4). Overall rankings for the study area were generated with a scoring system that allocated points for rankings at each state workshop. Six points were allocated for a top ranking, five points for a second place ranking, four points for a third place ranking, and so on. The overall ranking in Table 4.4 informed the selection of the attributes in the study.

There were substantial similarities between the states in terms of the rankings of potential attributes at the focus group meetings. Rural jobs and watershed protection were amongst the top attributes in each state. Notable differences in the top attributes were also found between the states. For example, reduced wildfire risk was the top ranked attribute in both Colorado and Arizona, but was not in the set of top attributes in Montana. Air quality was amongst the top attributes in both Montana and Colorado, but not in Arizona. Some apparent differences, however, may be an artifact of similar concepts being captured under different labels in different states. For example, although air quality was not amongst the top attributes in Arizona, reduced wildfire smoke was one of the top attributes, which may have captured some similar sentiments. Similarly, although forest restoration was not amongst the top attributes in Montana, “forest management” was in the top attributes, which captured increased ability to conduct management activities and restoration treatments.

There was enough similarity that it was possible to identify five attributes that were expected to resonate well across the entire study area. Therefore, findings from the multiple workshops were reconciled to create a single set of attributes to be presented to the respondents of all three study states. The five attributes selected were: rural jobs, number of large wildfires, local air quality, forest health, and number of homes powered with woody biomass energy. Although the ability to address climate change through increased renewable energy generation only ranked 8th most important overall, it was deemed an essential and policy relevant aspect of the issue that should be valued as part of the survey.

Table 4.4. Focus Group Workshop, Attribute Rankings from Participant Voting

Attribute	Missoula	Denver	Flagstaff	Overall
Rural Jobs	1	2	2	1
Reduced Wildfire Risk	nr *	1	1	2
Local Air Quality	3	4	nr *	3
Forest Management	2	nr *	nr *	4
Watershed Protection	6	5	5	5
Recreation	nr *	nr *	3	6
Hazardous Tree Removal	nr *	3	nr *	7
Climate Change/Alternative Energy	5	nr *	6	8
Reduced Wildfire Smoke	nr *	nr *	4	9
Energy Security	4	nr *	nr *	10
Forest Restoration	nr *	6	nr *	11

Note: * nr = Not ranked in the top 5.

4.2.2 Attributes and Attribute Levels

After the set of attributes was selected, an initial attempt was made at defining each attribute and selecting a metric with which to quantify changes in each attribute that would appear as differing levels in the choice sets. The definitions and suggested metrics were then sent to all focus group workshop participants, to receive feedback from them on whether an appropriate set of attributes were selected and about the clarity of the definitions. Participants were asked to comment on whether the definitions were informative, understandable, and unbiased, and whether the suggested metrics were an appropriate way in which to convey information about changes the attribute levels to survey respondents. Feedback was not as widespread among focus group participants as hoped but some useful feedback was received and used to refine and improve the attribute definitions.

Alternative levels for each attribute were also defined. Data was collected for each state in order to determine the status quo level for each attribute within each state. Attribute levels are shown in Table 4.5, and a detailed description of the estimation of status quo and alternative attribute levels is provided in Appendix B. The status quo levels of the attributes were similar across the three states so a common status quo was used across the entire study area.

Feedback from internal review of the survey instrument by peer experts suggested that, due to the complexity of the issue, including six attributes made the survey instrument overly burdensome for respondents. In order to reduce the complexity of the choice tasks, the rural jobs attribute was dropped from the survey. Although rural jobs was consistently ranked highly by focus group workshop, it was dropped because unlike the other attributes, there are market mechanisms available to value the impact of job creation and therefore the opportunity cost of leaving job creation out of the survey was lower than for the other attributes.

The temporal scope of the survey was a ten year time horizon. Respondents were asked about their willingness to pay for changes in their household energy bill over the next 10 years, in order to achieve changes in the attributes of which the decision problem was composed. Attributes were defined as ‘expected outcome over the next ten years’, to ensure a timeframe that was relevant for changes in forest management and policy, and was meaningful to respondents. For the most part, attributes were defined on a state-wide scale, so changes in attribute levels corresponded to changes in the quality or quantity of the environmental goods across the entirety of each respondent’s own state. An exception to this spatial scale is the definition of the air quality attribute, which was defined at a community scale. Although it would be preferable for all attributes to be defined in terms of the same spatial scale, it was believed that the local air quality experienced by respondents would resonate more strongly than a state wide air quality attribute.

4.2.2.1 Number of Homes Powered with Wood (HOMES)

The HOMES attribute captures WTP for offsetting fossil fuel use with a renewable energy source. The potential long-run climate change mitigation benefits of offsetting fossil fuel use with woody biomass was highlighted in the background information section of the survey instrument. Although a significant portion of the energy produced (and likely to be produced in the future) by woody biomass is not directly used to power households, the attribute was defined in terms of number of homes powered by wood because this is a metric which would be more easily interpreted by respondents than units of energy generation like kilowatt hours or British Thermal Units (BTUs) . The status quo level of woody biomass energy generated in each state was set 20,000 homes, with alternative levels of 10,000, 30,000, and 50,000 homes. The maximum level of homes was based on the estimated amount of woody biomass that could be sustainably produced by restoration treatments on public forests. HOMES was defined as: “a measure of the amount of woody biomass energy produced per year in your state over the next 10 years”. In the definition of the attribute, respondents were presented with the following facts to inform them about the attribute and its potential effects on respondents (see Appendix B for data sources):

- Currently the level of woody biomass energy produced in your state is equivalent to supplying the energy demands of 20,000 homes per year.
- 50,000 homes could be sustainably powered with woody biomass from restoration treatments in national and state forests in your state.

- This energy would be produced by a mixture of small-scale facilities, like those at schools and hospitals and large-scale power plants that put energy onto the electricity grid.
- This energy does <u>not</u> include heat produced by home wood stoves.

4.2.2.2 Local Air Quality (AIRDAYS)

The AIRDAYS attribute captures WTP to avoid degraded air quality in the respondent's local community. This attribute was defined as: "the number of days per year over the next 10 years when air quality in your community is unhealthy for sensitive groups". The status quo level for this attribute was based on data from the US EPA air quality monitoring sites at multiple locations throughout each state. Based on the average number of days annually across monitoring sites in the study states that were "unhealthy for sensitive groups", the status quo was set at 10. Alternative levels were set at 5, 15 and 30 unhealthy for sensitive groups air days per year. The AIRDAYS attribute was defined at the community scale, rather than at a state-wide scale because air quality varies widely from community to community and individuals are affected by their local air quality, not by the air quality of their entire state.

In the survey instrument, facts about the past status of air quality in communities in the respondent's state, and the potential health effects associated with air pollution were provided (see Appendix B for data sources). They were:

- On days when air quality is "unhealthy for sensitive groups", older adults and children, and persons with heart, lung or respiratory diseases are at risk of respiratory problems from the presence of particles in the air. The rest of the population may experience irritation of the eyes and nose, and an increase in the incidence of respiratory illnesses, including asthma.
- Communities in your state experienced an average of 10 days annually over the last 5 years with air quality that was unhealthy for sensitive groups.

- Long-term exposure to particulate air pollution can increase occurrence of certain types of cancers and heart problems, and reduce life expectancy for all members of the population, not just sensitive individuals.

- Increasing the number of days per year that are unhealthy for sensitive groups from 10 to 30 reduces life expectancy for the average person by about 30 days.

4.2.2.3 Number of Large Wildfires (WILDFIRES)

The WILDFIRES attribute captured WTP for reduced numbers of “large wildfires” and was defined as “the number of wildfires per year over the next ten years that burn at least 1000 acres and threaten homes and important watersheds in your state”. The attribute was focused specifically on fires that threaten human assets like homes and watersheds, and an attempt was made to disentangle the protection of human assets from the ecological and forest health effects of wildfires. Some of the facts presented to provide context for the wildfire attribute varied substantially between the states. Therefore, some state specific information was included in the definition that varied between states. The information provided in the Montana version of the survey is provided below. See Appendix B for data sources and statistics for Colorado and Arizona. The facts provided in the survey were:

- An average of 12 large wildfires have occurred annually in your state over the last ten years. However, the number of large fires that burn each year is highly variable, with the potential for high numbers in active fire years and zero in other years.

- On average over the past decade, 22 homes in Montana have been destroyed each year by large wildfires. Most were destroyed by a small number of very destructive fires.

- Large wildfires have damaged thousands of acres in important watersheds, requiring millions of dollars in restoration activities and water treatment costs.

- Even if your safety and family home are not at risk, those of some of your friends and relatives may be.

- Many large wildfires, like ones that burn in wilderness, do not destroy homes or burn important watersheds and are an important beneficial natural disturbance for healthy forest ecosystems.

4.2.2.4 Forest Health and Biodiversity Conservation (FORESTS)

The FORESTS attribute captured WTP for improved health in forests in each state. It was defined as: “the percent of healthy forestland in your state over the next ten years”. The levels were defined in terms of proportion of forestland in the state that is classified as healthy according to the Vegetation Condition Class (VCC) classification (US Department of Interior 2013). Healthy forests were defined as those that were not significantly departed from historic conditions, according to VCC. The attribute was represented in percentage terms, rather than in terms of absolute acres because percentage was believed to be more easily interpreted. Additionally, although the three study states varied significantly in both total amount of forestland, and amount of healthy forestland, the relative proportions of healthy forestland across the states was similar enough to allow for a common status quo level to be used across the three states. The following facts provided context for the attribute definition (see Appendix B for citations):

• Today approximately 20% of forestland in your state is classified as healthy. As a result of fire exclusion, poor timber harvesting practices in the past and livestock grazing, the remaining 80% is not classified as healthy.

• Healthy forests support a greater diversity of native plant (trees, shrubs and grasses) and animal species (predators, small mammals, birds and insects), and are better able to bounce back from human and natural disturbances like insect outbreaks, non-native species invasion, disease, uncharacteristic wildfires and a changing climate.

4.2.2.5 Household Average Monthly Energy Bill (BILL)

The payment vehicle was defined in terms of respondent average household monthly energy bills over the next 10 years. The annual equivalent of BILL was also provided in the choice sets to decrease the likelihood of respondents interpreting the monthly amounts as inconsequential. In the questionnaire the following pieces of information are provided in the attributes definition (citations for data sources are provided in Appendix B):

- If the current energy mix in your state does not change, the average household energy bill is expected to be about $100 per month over the next ten years.

- If a larger percentage of energy produced in your state comes from woody biomass, your energy bills are likely to be higher because of high harvest and transport costs for wood.

- However, when combined heat and electricity production are possible, and when woody biomass is available in large quantities close to power plants, woody biomass energy may be less expensive than other energy sources, resulting in lower energy bills.

- For alternatives with higher energy costs, consider what part of your household budget would be cut to pay for higher energy bills. For lower energy cost alternatives, consider where extra household income might be spent or saved.

4.2.3 Experimental Design Development

The experimental design for the choice experiment was generated using SAS statistical analysis software, using macros described in Kuhfeld (2010). First, the MktRuns macro was used to determine a reasonable size for the experimental design. The number of attributes and levels (shown in Table 4.5) were used to parameterize the MktRuns macro. Based on these parameters, the macro calculated that the full factorial design of would consist of 1,536 ($4^4 \times 6^1$) alternatives and suggested design sizes of 48 and 96 alternatives with zero violations of orthogonality and the potential to create 100% efficient design using the MktEx macro. A completely efficient design is balanced (each level appears equally often in the design) and orthogonal (each pair of levels appears equally often across all pairs of attributes) (Johnson et al. 2013). Depending on the number of attributes and levels, a completely efficient design is not always possible. The efficiency of an experimental design in terms of balance and orthogonality can be assessed using A-efficiency, D-efficiency, or G-efficiency (Kuhfeld 2010). D-efficiency is the most commonly used measure of efficiency because it is less computationally intensive and allows comparison between competing designs with different coding schemes (Kuhfeld 2010). Although both the 48 and 96 combination design sizes offered the opportunity to create an efficient design, the 48 combination design was selected to minimize the number of alternative that would need to be included in the survey.

Table 4.5. Attribute Levels

	Level						
Attribute	a	b	status quo	d	e	f	g
AIRDAYS		5	10	15	30		
WILDFIRES	6	9	12	15			
FORESTS		10	20	30	60		
HOMES		10000	20000	30000	50000		
BILL		80	100	120	150	200	400

Next, based on the efficient number of alternatives (48), the MktEx macro was used to create the full factorial design with 1536 alternative profiles to be used as an input for the creation of the efficient fraction factorial design. The Choiceff macro was then used to create an efficient design based on the candidate set of 1536 (plus the status quo) alternatives. The Choiceff macro was parameterized with the desired number of choice sets (24) and the number of non-status quo alternatives per choice set (2) (total of 48 alternatives). The result was an experimental design with 24 pairs of alternatives and a status quo option was added to each pair to complete the choice sets. The experimental design had an associated relative D-efficiency measure of 59.7.

With the 24 choice sets constructed, Mktblock was used to block the choice sets into 6 blocks, each containing 4 choice sets. The choice sets were then manually inspected for dominant alternatives in which all rational respondents would always prefer one of the alternatives to the others. The presence of such an alternative in a choice set means the choice set provides no information about the willingness of respondents to trade-off attributes. Three choice sets were found to have a dominant alternative and were manually adjusted to create a more informative tradeoff. Respondents were randomly assigned a questionnaire with one of the six blocks of choice sets.

4.2.4 Choice Modelling Survey Instrument

The 16-page survey instrument contained four sections. Section 1 provided a short introduction and collected information about respondent residence and opinions about energy generation, public land management, and climate change. Section 2 provided background information about energy consumption in the US, forest restoration treatments, and details about what woody biomass energy is, how it is generated, sustainable levels of production from public forests in the three states, and the costs and benefits associated with biomass harvesting and energy generation from biomass. The preliminary questions in sections 1 and 2 served to characterize respondent attitudes and beliefs, as well as preparing respondents to consider their options in the choice sets. Section 3 defined the attributes and presented the respondent with one block of four choice sets. Respondents were reminded to consider their budget constraints and alternative uses of their income. Section 4 collected information about the respondents' experience with the survey and sociodemographic information, which allowed comparison between the collected sample and the general population of the state.

A copy the survey questionnaire can be found in Appendix C. The questionnaire was 16 color pages, either in a paper booklet or in an on-line layout. First there was an introduction. It was followed by a section of questions about attitudes towards energy production, climate change, public land management, and broad issues of national concern. Next, an information section provided background information on US energy consumption, what biomass is and how it can be used to generate energy, and some of the potential costs and benefits associated with woody biomass energy generation. Pictures were included on the cover page with the introduction and interspersed throughout the information section, in order to make the text less monotonous and hold the respondents' attention. Following the information section, the attributes were defined and instructions provided for completing the choice sets.

Because the experimental design requires that a wide variety of attribute level combinations appear in the choice sets, a statement was made reinforcing the fact that any combination of attribute levels is possible, even if they seemed unlikely to the respondent. Respondents were informed that changes in the level of each of the non-energy attributes were not necessarily tied to a corresponding change in the level of woody biomass energy because factors aside from the level of woody biomass energy can also influence future outcomes of the other attributes. For example, in addition to emissions from energy generation, air quality can be affected by wildfires, prescribed burning, pile-burning of residues, and other sources of emissions. The number of large wildfires varies considerably from year to year and can be affected by drought and climate change. Biomass harvest can have either positive or negative effects on forest health depending on forest-type and harvesting practices.

Next, the four choice sets were presented. Choice sets were laid out as a table, with alternatives presented as columns and attributes laid out in rows. Each choice set contained a status quo option, and two alternative profiles, for a total of three alternatives. The alternatives were composed of five attributes, including a payment mechanism. Attributes were presented on the far left of the table, along with a corresponding picture that was chosen to capture the essence of the attribute and resonate with respondents. The picture associated with each attribute was also presented with the attribute's definition in order to help respondents recall the information provided in the definition while completing the choice set. The alternative profiles were labeled either as "current strategy" or as an alternative strategy labeled with a letter like "strategy A" or "strategy B". Each alternative column was shaded a different color to help respondents distinguish between alternative profiles. Finally, there was a section of debriefing questions about respondent experience with the survey, and sociodemographic information collection.

4.2.5 Sampling Strategy and Data Collection

Data collection was contracted out to the Bureau of Business and Economic Research at the University of Montana (BBER). A goal of 1,200 responses (400 per state) was based on the sample size needed to achieve an acceptable amount of sampling error, based on the size of the study population (see Dillman 2007 for a complete table of sample sizes needed for various population sizes and desired levels of precision). The sample was stratified to ensure coverage of people who live in forested areas and people who live in airsheds with a history of poor air quality because these characteristics were hypothesized to affect preferences toward the attributes of interest. The stratifications can be seen in the study area map (Figure 4.1).

Residents of forested areas were identified using a geographic information system (GIS) and spatial data of US EPA level III Ecoregions (EPA 2013). Forested Ecoregions in the study area are: Northern Rockies, Middle Rockies, Southern Rockies, and Arizona/New Mexico Mountains (EPA 2013). Residents of forested ecoregions were expected to have stronger preferences toward the WILDFIRES and FORESTS attributes because of their proximity to forestland.

Poor air-quality airsheds were identified as EPA non-attainment airsheds, which have failed to meet national ambient air quality standards. Residents of non-attainment airsheds were expected to have stronger preferences toward the AIRDAYS attribute because of their higher levels of experience with poor air quality.

In addition, because of the large number of Spanish speaking residents in Arizona and Colorado, for census tracts with at least 50% Hispanic population, respondents were provided with the option of completing a Spanish language version of the survey. The Spanish language survey was developed by two professional translators. The translation began with one of the translators translating the English version of the survey into Spanish. The second translator then translated the Spanish language survey back into English. Finally, in order to ensure the accuracy of the Spanish language version, both translators and the PhD candidate reviewed the two English versions of the survey to check for differences that indicated inaccuracies in the translation. The Spanish language version was then updated to remedy inaccuracies.

A pre-test of the survey instrument was conducted in Missoula, Montana on July 1st, 2014. The pre-test was conducted at the Southgate Mall, where shoppers were intercepted by the researches and asked to fill out the survey, as if it they had received it at their residence. After completing the survey, the volunteers were asked to provide feedback on the length, content and clarity of the survey. Shoppers were given a $10 gift certificate to the mall as a token of appreciation for their participation. Based on feedback from the pre-test, modifications were made to the survey to reduce complexity and increase clarity, including reducing the number of non-price attributes from five to four. Some detailed information on climate change, including the roles of biogenic and geologic carbon in the terrestrial carbon cycle was also removed to reduce the complexity of the survey instrument.

4.2.6 Survey Contact Modes

A mixed-mode data collection strategy was employed in order to compare the effectiveness of data collection with alternative survey modes. Respondents were contacted with an invitation letter mailed to their home explaining the purpose of the research and randomly presented with one of the following response options: (a) a web address and unique identification (ID) number that served as a password to complete the survey online, (b) a notification that they would soon be receiving a physical survey packet in the mail, or (c) both a web address with ID number *and* the option to wait and receive a physical copy of the questionnaire in the mail if they did not respond online. Individuals in the online-only group (a) who had not completed the survey after about two weeks received a reminder post-card in the mail. Individuals in the other two survey groups (b and c) were contacted using the four-contact method described in Dillman (2007), which is designed to maximize response rate and minimize non-response bias. Mixed-mode respondents did not receive the $2 bill incentive that the mail-only respondents received.

4.2.7 Response Rates and Respondent Characteristics

The survey yielded 1,226 total complete returned surveys. As shown in table 4.6, the mail-only survey mode had the highest effective response rate, at 42%. The response rate for the mixed-mode was 39%. Of the 345 responses to the mixed-mode survey, 291 responses were completed with mail hard-copy and 54 were completed on the internet. At 4.5%, the internet-mode had the lowest response rate. The lower response rate for mixed-mode than the mail-only may be a result of the $2 incentive that was provided in the mail-only contact material, and not in the mixed-mode material. Incentives have been shown to produce higher response rates (Mooney et al. 1993). Response rates were highest in Montana and lowest in Arizona, across all survey modes. Higher response rates in Montana may have been the results of higher name recognition of The University of Montana.

Table 4.6. Response Rates by Mode

	Internet	Mail	Mixed
Invitations sent	16,775	511	1,019
Undeliverable invitations	1,451	57	125
Delivered invitations	15,324	454	894
Complete responses	692	189	345
Overall response rate	**4.5%**	**42%**	**39%**
MT response rate	5.9%	54%	50%
CO response rate	4.5%	35%	36%
AZ response rate	3.1%	35%	29%

Overall, the survey respondents were on average older, better educated, and wealthier, and more likely to be male than residents of the study area as a whole (Table 4.7). The mean age of respondents was between 55 and 59 years old. The mean household income was between $50,000 and $75,000. The sample is disproportionately White, and substantially less Hispanic, than the study area as a whole. The use of a bi-lingual survey in counties with high proportion of Hispanic residents did not result in a significant amount of surveys completed in Spanish. Only five Spanish language surveys were returned. Respondents were identified as either urban or rural based on the classification of metro and non-metro counties as defined by the US Economic Research Service (ERS 2015)[4]. Respondents were less likely to live in urban areas than the population of the study area as a whole. Throughout the entire study area, 87% of people live in metro counties. While in the collected sample, 66% of respondents live in metro counties. However, the proportion of urban residents varied significantly between states, with only 35% of the population in Montana residing in metro counties, and 86% and 95% in metro counties in Colorado and Arizona (ERS 2013).

[4] Metro counties are defined in two ways (1) core metro counties are ones that contain at least one densely-settled urban area with 50,000 or more people, and (2) outlying metro counties that are economically tied to the core counties, as defined by at least 25% of workers in the county commuting to a core county, or at least 25% of the employment in the county consists of workers commuting from a core metro county.

Table 4.7. Sociodemographic Characteristics of Sample and Population

Variable	Collected Sample (%)	Population (%)
Age [b] (mean 55-59)		
18 – 29	2.2	13.9
30 – 39	10.3	12.8
40 – 49	11.9	13.7
50 – 59	22.2	13.8
60 – 69	23.5	10.1
70 - 79	16.8	5.6
80 +	4.1	3.5
Gender [a]		
Male	68.0	50
Female	32.0	50
Income [b] (mean 50 – 70k)		
< $15,000	2.7	13.0
$15,000 - $35,000	13.6	21.3
$35,000 - $50,000	16.3	14.2
$50,000 - $75,000	20.8	18.6
$75,000 - $100,000	17.0	12.5
$100,000 - $200,000	21.6	17.3
> $200,000	6.1	4.1
Educational attainment [a]		
< high school diploma	1.3	12.2
high school diploma	25.2	29.6
bachelor's degree	29.7	19.2
graduate degree	31.0	10.6
Race & Ethnicity [b]		
White	92.5	64.3
Hispanic or Latino	3.2	24.4
Black or African American	0.7	4.2
Asian	0.7	2.9
American Indian or Alaska Native	2.7	3.9
Native Hawaiian of Pacifica Islander	0.3	0.2

Notes:
a: Population source: Census Bureau (2015). Age and education proportions for population are national statistics. Youngest age category is for age 20-29, rather than 18-29, as in the respondent proportions.
b: Population source: Census Bureau (2014). Based on the weighted average of the populations in AZ, CO, & MT.

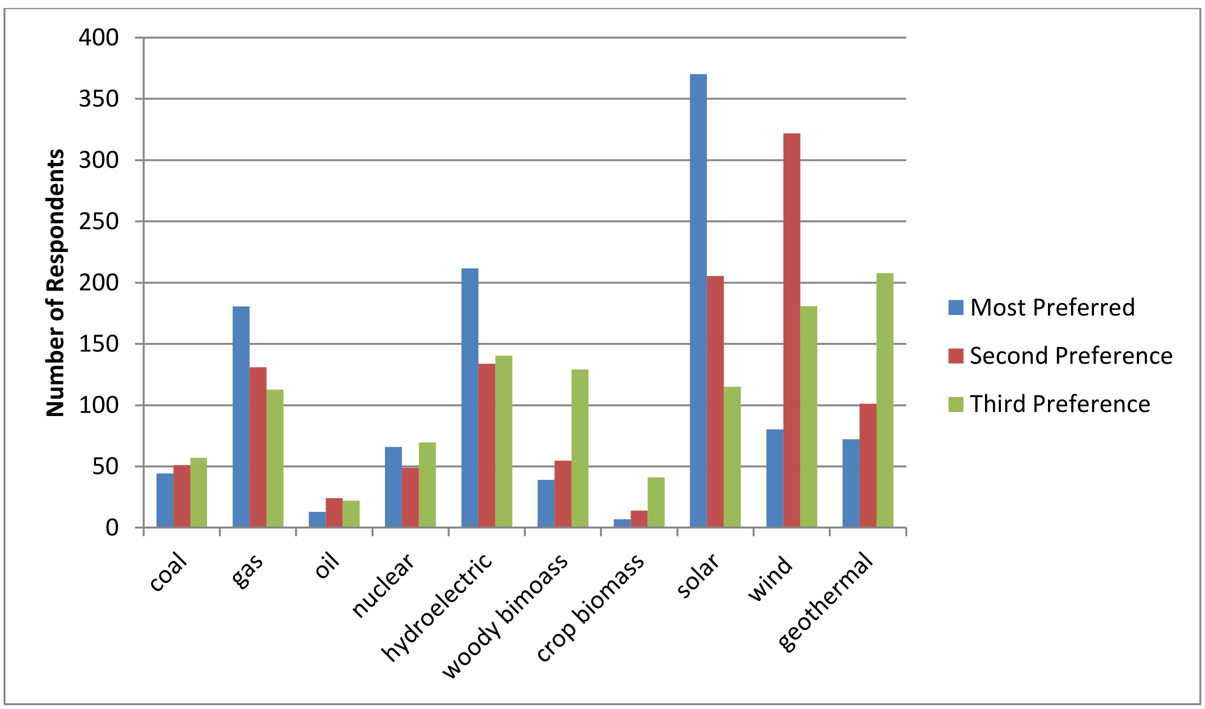
Preliminary questions revealed that respondents have an interest in issues related to the attributes in the choice sets (Table 4.8). A large majority of respondents agreed that public forests are in need of restoration, to conserve biodiversity, reduce risk of large wildfires, or minimize the impacts of insect and disease infestation. Respondents expressed concerns related to air quality, with 66% of respondents indicating that smoke from wildfires and the burning of slash piles negatively affected the health of people in their community, and 66% of people agreeing that air pollution from cars, industry, power plants and wood stoves negatively affected the health of people in their community.

Table 4.8. Attitudes Toward Forest Management, Air Quality and Energy Policy

Statement	Respondents who Strongly or Somewhat Agree (%)
Public forests are in need of restoration treatments to conserve biodiversity	83.2
Public forests are in need of restoration treatments to reduce the risk of large wildfires	90.2
Public forests are in need of restoration treatments to minimize impacts from pests and disease	87.7
Creation of rural jobs should be an important consideration in the management of public forests	64.2
I support greater utilization of woody biomass from public forests for energy	75.8
I would support a large-scale woody biomass energy facility that puts electricity onto the grid in my community	59.2
I would support small-scale woody biomass energy facilities to power buildings like schools or hospitals in my community	74.9
Smoke from wildfires and burning of brush and slash piles affects the health of people in my community	65.5
Air pollution from cars, industry, power plants and fire places and wood stoves affects the health of people in my community	65.8
Utility companies should be required to produce more renewable energy	69.7
I support more renewable energy production to reduce greenhouse gas emissions	77.0
I would be willing to pay higher monthly energy bills for renewable energy	49.8
I would be willing to pay higher monthly energy bills for locally produced energy	44.2
I support expanded exploration for coal, oil and natural gas	45.2

Responses to questions about biomass harvest and energy generation revealed generally positive attitudes. For example, a majority of respondents (76%) indicated that they supported higher amounts of woody biomass harvest from public lands to generate energy. Respondents also indicated that they would support biomass energy facilities in their community. Support was higher for small scale biomass energy facilities like ones used to heat schools (75%), than large-scale woody biomass energy facilities that put electricity onto the power grid (59%). However, respondents were less enthusiastic about woody biomass energy in relation to other energy options (Figure 4.3).Based on a weighted sum of 1st, 2nd, and 3rd place rankings[5], woody biomass was ranked 6th in preference out of ten options when asked to rank their top three sources of household energy. Solar was the most popular energy option. Wind (2nd), hydroelectric (3rd), natural gas (4th), and geothermal energy (5th) also received more support than woody biomass energy. Woody biomass energy was ranked ahead of nuclear energy (7th), coal (8th), oil (9th), and crop biomass (10th).

Figure 4.3. Preferred Sources of Household Energy



[5] Each 1st place ranking received three pointes. Each 2nd place ranking received two points. Each 3rd place ranking received one point.

4.2.7.1 Investigation of Nonresponse Bias

Nonresponse bias can arise in survey research if the people who respond to the survey differ systematically from the people who did not respond. This can occur for reasons such as people with stronger opinions about the topic perhaps being more likely to respond. Nonresponse bias can be mitigated by minimizing nonresponse itself through maximizing overall response rates (Lohr 1999). The Dillman (2007) four-contact method was used to maximize response rate from the mail-only and mixed survey modes in this study. Even if strong response rates are achieved, it can be difficult to estimate nonresponse bias because is difficult to know the characteristics of people who chose not to respond to the survey. One way of assessing whether non-respondents differ systematically from respondents is to compare the characteristics of those who responded later with those who responded earlier, based on the assumption that late-responders are more similar to non-responders than early respondents (Armstrong and Overton 1977).

In this study, late responders where identified as those who responded only after receiving the reminder post card, and they represent 40% of respondents. Other definitions of late responders were examined, including people who responded only after receiving the second packet, but that represented a small proportion of respondents and was deemed less informative. Comparison of sociodemographic and attitudinal characteristics reveals that late respondents differed significantly from non-late respondents in some ways (Table 4.9). Late-responders were significantly less likely to be male, senior citizens, high income earners, or have a college degree. They were also significantly less likely to believe in anthropogenic climate change, or believe that public forests are in need of restoration, which suggests that the survey topic may have resonated less with late-responders.

Because significant differences were found to exist between late-responders and other respondents, there is some evidence that non-respondents may differ from respondents. In order to assess whether these potential differences may have created bias in the results of the econometric analysis, MWTP for the choice attributes was estimated for late-respondents and non-late respondents separately. These results are presented in Appendix D, Table D.4. Although not a statistically significant result, one finding of note is that MWTP for HOMES by late-respondents is not statistically different from zero, but is positive and significant for non-late respondents. However, no statistically significant differences are found between the preferences of late-responders and others in terms of MWTP (95% confidence intervals overlap for all attributes). Therefore, although the differences in characteristics between late-responders and other respondents suggests that there may be differences between respondents and non-respondents, there is no significant evidence that these differences are tied to differences in preferences toward the attributes in the survey.

Table. 4.9. Mean Value of Sociodemographic Characteristics by Mode and Study Area Population

Characteristic	Late	Not-Late	Population	Test Statistic
MALE	52%	69%	50%	Pearson chi2= 438.4, pr=0.000
SENIOR	31%	38%	14%	Pearson chi2= 77.2, pr=0.000
HIGHINC	22%	26%	20%	Pearson chi2= 39.2, pr=0.000
COLLEGE	48%	59%	31%	Pearson chi2= 156.9, pr=0.000
SKEPTIC [a]	50%	47%	49%	Pearson chi2= 18.0, pr=0.000
RESTORATION [b]	85%	90%	NA	Pearson chi2= 85.1, pr=0.000

Notes: a: SKEPTIC represents respondents who indicated that they do not believe in anthropogenic climate change.
b: RESTORATION represents respondents who indicated that they thing public forests are in need of restoration.

4.3 Chapter 4 Summary

Chapter 4 provided a description of the study area, described the steps used to implement the choice modeling survey, and presented information about response rates and respondent characteristics. Geographic, sociodemographic and ecological characteristics of the study area highlight the relevance of woody biomass energy in the Mountain West. The methods used to carry out the choice modeling exercise demonstrate the substantial amount of time and effort that was put into developing a high-quality survey. Response rates to the survey modes were good and the target sample size was achieved. Evidence of significant differences between late responders and others in the collected sample was found. However, worries about non-response bias in the data are minimized because no significant differences in preferences were found between these groups. Results from econometric analysis of the data collected in the survey are presented in Chapters 5, 6 and 7.

4.4 Chapter 4 References

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Chapter 5

Social Preferences toward Energy Generation with Woody Biomass from Public Forests in Montana, USA

Abstract:

In Montana, USA, there are substantial opportunities for mechanized thinning treatments on public forests to reduce the likelihood of severe and damaging wildfires and improve forest health. These treatments produce residues that can be used to generate renewable energy and displace fossil fuels. The choice modeling method is employed to examine the marginal willingness of Montanans' to pay (MWTP) for woody biomass energy produced from treatments in their public forests. The survey instrument elicited social preferences for important co-benefits and costs of woody biomass energy generation in Montana, namely the extent of healthy forests, the number of large wildfires, and local air quality. Positive and statistically significant MWTP is found for woody biomass energy generation, forest health and air quality. MWTP to avoid large wildfires is statistically insignificant. However, MWTP for woody biomass energy diminishes quickly, revealing that Montanans do not support public forestland management that produces more than double the current level of woody biomass harvested for energy generation. These findings can be used by policy makers and public land managers to estimate the social benefits of utilizing residues from public forest restoration or fuel treatment programs to generate energy.

5.1. Introduction

In 2009, about 83% of energy consumed in the United States came from coal, oil and natural gas (EIA 2010). In order to reduce greenhouse gas emissions and reliance on imported fossil fuels, the United States government has passed legislation aimed at decreasing fossil fuels use through increased efficiency and increased production of renewable solar, wind, hydroelectric, geothermal and biomass energy (United States Congress 2005, United States Congress 2007). About 2% of all energy generated in the United States, representing 24% of renewable energy, presently comes from woody biomass (EIA 2010), and studies have found that woody biomass could potentially supply up to 10% of US energy needs (Zerbe 2006). A major barrier to expansion of woody biomass energy in the US has been its high production cost relative to fossil fuels (Gan and Smith 2006). However, there are significant negative externalities created by the extraction, transport, and combustion of fossil fuels for energy generation (National Academy of Sciences 2010) and potential positive externalities associated with woody biomass energy that, if accounted for, may make woody biomass energy a socioeconomically efficient component of the energy portfolio in the US.

In order to place a dollar value on the externalities associated with energy generation, nonmarket valuation techniques are required. Nonmarket valuation studies have been used to quantify the value of a wide range of environmental goods and services associated with renewable energy generation, including reduced greenhouse gas emissions (Roe et al. 2001, Longo et al. 2008, Solomon and Johnson 2009, Susaeta et al. 2011, Solino et al. 2012), improved air quality (Roe et al. 2001, Bergmann et al. 2006), enhanced preservation of landscape quality (Álvarez-Farizo and Hanley 2002, Bergmann et al. 2006), reduced wildfire risk (Bergmann et al. 2006, Solino et al. 2012) and preservation of wildlife habitat and biodiversity (Álvarez-Farizo and Hanley 2002, Bergmann et al. 2006). Positive willingness to pay (WTP) has also been found for non-environmental attributes including energy security (Longo et al. 2008, Li et al. 2009) and rural employment (Solino et al. 2012).

Few studies to date have attempted to value externalities associated with woody biomass energy generation specifically. Susaeta et al. (2011) used a choice modeling exercise to assess preferences toward externalities associated with woody biomass energy in Arkansas, Florida, and Virginia. Respondents had positive (but statistically insignificant) WTP for improved forest health, reductions in CO_2 emissions and improvement of forest habitat from reduced wildfire risk. Because almost 90% of forest lands in the Southern US are privately owned, little of the woody biomass described in the Susaeta et al. (2011) study would come from public lands. In the absence of financial incentives, including markets for carbon, applications of the findings of this study to inform and influence private forest management and woody biomass energy generation appear limited. Solino et al. (2012) found positive WTP in Spain for reduced greenhouse gas emissions, reduced risk of forest fire and reduced pressure on natural resources associated with the utilization of woody biomass for electricity generation

The US west has unique geographic, ecological, and socioeconomic characteristics - perhaps the most significant of which in this context is the high proportion of public lands compared to other parts of the country. For example, over one-third of the land area of the US state of Montana is owned by the state and federal governments. No past studies have evaluated social preferences regarding woody biomass energy in the western United States, nor have previous studies evaluated preferences specifically toward feedstock generated by forest restoration treatments on public forests. This is an important distinction because optimal decision making with regards to biomass harvesting differs between private landowners and social planners because of differences in private and social accounting of other amenities provided by forests (Hallmann and Amacher 2014). Additionally, compared to landscapes dominated by private ownership, public preferences are more relevant to, and can be more readily accommodated within, forest management and policy in the western United States.

This study used choice modeling to examine public preferences toward the utilization of woody biomass from public forests for energy generation in Montana. Preferences were characterized in terms of WTP for increases in energy generated with woody biomass harvested from public forests and for potential effects of changes in public forest management on forest health, the prevalence of large wildfires, and air quality. By determining public willingness to trade-off woody biomass energy generation against important environmental attributes, the results of this study can inform public forest management and renewable energy policy in Montana.

The paper proceeds with a description of the geographic and socioeconomic characteristics of the study area, followed by a description of the development of the survey instrument. The econometric model used to analyze the data is presented next, followed by the results of the study, and finally, the study's main findings and implications.

5.2. Study Area and Co-Benefits and Costs of Woody Biomass Energy

Montana's economy has historically relied heavily on agriculture and resource extraction through logging and mining, and the forest industry still accounts for a significant portion of economic activity in several counties in the state (McIver et al. 2013). As has been the trend throughout the rural West, Montana's economy is increasingly service oriented, fueled by tourism and migration based on natural amenities provided by the state's public lands, and recreational opportunities (Rasker and Hansen 2000). Montana is home to multiple national parks and national forests, which were the main attraction for 11 million of the state's visitors in 2013 (Grau et al. 2014). The state has a large, and expanding wildland-urban interface that allows residents to live among the natural amenities they desire, but also places their lives and homes at risk from wildfires (Rasker 2014).

Of the 9.4 million hectares of forestland in Montana, 3.8 million are classified as moderately or severely departed from natural fire regimes. Forests that are departed from historic fire regimes have increased tree density, structural homogenization, and fuels buildup (Taylor 2004), resulting from decades of wildfire suppression (Ryan et al. 2013). Forests in these conditions are less able to support native plant and animal species (Huntzinger 2003, Hiers et al. 2007), are less resilient to disturbances like insect and disease infestation, and more likely to experience unusually severe and damaging wildfires (Schwilk et al. 2009). Forest managers typically mitigate such conditions using mechanized thinning treatments, prescribed wildland fire, or a combination of the two (Rummer et al. 2005). Prescribed fire uses controlled human-ignited fire under favorable weather and fuel conditions to burn excess fuels without igniting the boles and crowns of dominant trees. In contrast, mechanized thinning treatments use heavy equipment to remove and process these fuels, sometimes generating merchantable forest products like sawlogs, pulpwood and woody biomass, which is defined in this context as the limbs, tops, needles, leaves, and other parts of trees and woody plants that are generated as the byproducts of forest management.

Some forestland can be treated with prescribed fire alone, but in cases where very high fuel loads are present, air quality restrictions are in place, or the forest is in close proximity to developed areas, mechanized treatments may be required before, or in place of, prescribed fire (Rummer et al. 2005). Prescribed fire or mechanized forest restoration treatments can increase the area of healthy forests that support a greater diversity of native plant and animal species, and are more resilient to human and natural disturbances like insect outbreaks, non-native invasive species, disease, wildfires and a changing climate (Swanson et al. 1994, Barrett et al. 2012). These treatments can also reduce the severity of large wildfires (Stephens et al. 2009) that can burn homes, damage important municipal watersheds, endanger firefighter and civilian lives, and blanket large areas with wildfire smoke. There is some evidence that, as a result, such treatments result in future fire suppression cost savings, but this effect is difficult to quantify (Thompson and Anderson 2015).

Woody biomass from timber harvest and fuel treatment is currently used as fuel to generate energy in a number of facilities in Montana, producing 201,000 megawatt hours (MWh) of energy annually (DNRC 2011, McIver et al. 2013). The majority of this energy is produced by lumber mills that utilize biomass residues created by logging and milling processes to heat and power their facilities, and in one case, to supply electricity to the power grid. Residues from the forest sector are also used to fuel wood heating systems in ten schools and other public buildings throughout the state as part of the United States Department of Agriculture's (USDA) "Fuels for Schools" program. In a case study of one of these wood heating systems, Bergman and Maker (2007) found that the system saved money on fuel costs, with an expected payback period of just under ten years.

Federal legislation like the Healthy Forests Restoration Act of 2003 mandates the federal government to increase the amount of timber harvest and restoration treatment in public forests, and encourages harvesting woody biomass for energy generation (United States House of Representatives 2003). Mechanized forest restoration treatments typically cut small diameter, subdominant trees with little or no value in traditional timber markets. A woody biomass energy market would provide an outlet for this material and provide revenues to offset the cost of treatments. Additional woody biomass energy generation would also contribute to achieving compliance with the state's renewable energy portfolio standard, which mandates that public utilities and other competitive electricity suppliers serving 50 or more customers obtain at least 15% of their retail electricity from renewable sources as of 2015 (United States Department of Energy 2015). However, harvesting woody biomass can also have a negative effect on forest health and biodiversity through reduced soil productivity (Thiffault et al. 2011), increasing opportunities for the spread of invasive weeds, and increasing sediment runoff into streams (Shepard 2006). Additionally, in communities where woody biomass facilities are located, local air quality may be negatively impacted (Chum et al. 2011).

5.3. Choice Modeling Survey Instrument

Choice Modelling is a stated preference non-market valuation technique that allows researchers to estimate the economic values of a set of multiple, divisible attributes, associated with an environmental good. Public preferences toward each attribute are revealed by the choices that survey respondents make when presented with different states of the environmental good, as defined by varying levels of the attributes of which the good is comprised. The various states of the environmental good are generated using statistical experimental design and presented in choice sets that provide multiple alternative scenarios and a status quo option from which respondents must select their preferred state of the world, and in the process, make trade-offs between the levels of the attributes. The inclusion of a price attribute allows for the estimation of WTP for the individual attributes.

Because significant economic benefits are derived from the timber and amenities of Montana's public forests, residents are likely to have strong preferences about public land management policy and practice. In order to determine which socioeconomic and environmental effects associated with woody biomass energy generation are most important to residents of Montana, a focus group meeting was held in Missoula, Montana, in July of 2013. The meeting was attended by stakeholders from the United States Forest Service (USFS), Montana Department of Natural Resources, Montana Department of Environmental Quality, The University of Montana, The Montana Wilderness Association, the forest industry, wildlife and land conservation groups, and local recreation groups.[6] The five most important attributes associated with woody biomass energy identified at this meeting were: homes powered with wood in the state (abbreviated HOMES); unhealthy air days experienced locally (AIRDAYS); large wildfires in the state (WILDFIRES); forest health in the state (FORESTS); and household monthly energy bill (BILL).[7] Each attribute was defined over a ten-year time horizon to provide a realistic time-frame in which to adopt and implement new forest management strategies, while also remaining relevant to respondents. The attributes are defined together with their status quo and alternative levels in Table 5.1. Quadratic transformations for the choice attributes, also shown in Table 5.1, are included in statistical models to account for non-linearity in relationships between the attribute levels and likelihood of selecting a particular alternative.

Table 5.1. Definitions of choice attributes and quadratic variables

Variable	Definition	Levels	Units
Choice attributes			
HOMES	The amount of electric or thermal energy produced from woody biomass produced annually in MT, using residues from restoration treatments on public forests.	10000, 20000*, 30000, 50000	Homes per year
AIRDAYS	The number of days per year when air quality is unhealthy for sensitive groups in your community.	5, 10*, 15, 30	Days per year
WILDFIRES	The number of wildfires per year that burn at least 1000 acres and threaten homes and watersheds in MT.	6, 9, 12*, 15	Wildfires per year
FORESTS	The percent of healthy forestland in MT, across all forest ownership categories.	10, 20*, 30, 60	Percent
BILL	Household average monthly energy bill in MT in US dollars.	80, 100*, 120, 150, 200, 400	US dollars
Quadratic variables			

[6] Representatives from tribal forestry, private forest owners, and environmental groups with a strong anti-biomass energy stance were contacted about attending the meeting, but were either unavailable or uninterested in attending the meeting.

[7] A sixth attribute, "Rural Job Creation" was ranked as important and initially included in the survey, but was dropped after peer-review suggested that the survey was overly-complex. "Rural Job Creation" was dropped, rather than one of the attributes, because the economic value of job creation can be estimated from markets, while the other attributes are not presently traded in markets.

HOMES_SQ	Squared value of HOMES
AIRDAYS_SQ	Squared value of AIRDAYS
WILDFIRES_SQ	Squared value of WILDFIRES
FORESTS_SQ	Squared value of FORESTS

* indicates status quo attribute level

HOMES was used as the metric for biomass energy production based on feedback from focus group participants. It was determined that the number of homes powered would be more easily interpreted than a unit of electric or thermal generation, such as kilowatt hours (kWh) or British thermal units (Btus). The woody biomass energy produced was defined as replacing energy that is currently produced using fossil fuels, and the ability to offset fossil fuel use and reduce long-term impacts of climate change was presented as a benefit associated with HOMES.

AIRDAYS was based on the average number of days from 2008 through 2012 that air quality was documented as "unhealthy for sensitive groups" at United States Environmental Protection Agency (EPA) monitoring stations throughout the state, representing the average number of days the average Montanan household is exposed to levels of air pollutant concentrations that are high enough to pose a health risk to older adults, young children and people with specific health concerns (EPA 2013). The definition explained that long-term exposure to the concentrations of particulate matter present when air quality is "unhealthy for sensitive groups" may pose health risks to all members of the community and reduce life expectancy (Pope et al. 2009).

The WILDFIRES status quo level was determined using a GIS data set from the Monitoring Trends in Burn Severity project (MTBS 2012). The definition highlighted the average number of homes destroyed annually over the past decade in Montana, but also stressed that the majority of homes were destroyed by a small number of very destructive fires, that the number of fires each year is highly variable, and that wildfires are an important beneficial natural disturbance present in healthy forest ecosystems.

The FORESTS definition emphasized the fact that healthy forests support a greater diversity of native plant and animal species and are more resilient to disturbances. The proportion of healthy forests in Montana was determined using the Vegetation Condition Class classification system, which categorizes the level of departure of current vegetation conditions from a historic reference (Barrett et al. 2010). This proportion includes all forested lands across all ownerships.

BILL, the average monthly household energy bill in Montana was used to define the status quo of the cost attribute (EIA 2011). This bill includes both electricity and natural gas, or other fuel for heat. Energy bill is an obligatory payment mechanism that is less likely to induce protest responses than a government tax or fee. The annual equivalent of BILL was also provided in the choice sets to decrease the likelihood of respondents interpreting the monthly amounts as inconsequential.

Because the experimental design requires that a wide variety of attribute level combinations appear in the choice sets, a statement was made reinforcing the fact that any combination of attribute levels is possible, even if they seemed unlikely to the respondent. Respondents were informed that changes in the level of each of the non-energy attributes were not necessarily tied to a corresponding change in the level of woody biomass energy because factors aside from the level of woody biomass energy can also influence future outcomes of the other attributes. For example, in addition to emissions from energy generation, air quality can be affected by wildfires, prescribed burning, pile-burning of residues, and other sources of emissions. The number of large wildfires varies considerably from year to year and can be affected by drought and climate change. Biomass harvest can have either positive or negative effects on forest health depending on forest-type and harvesting practices.

There are 1,536 possible combinations of the attributes and their levels ($4^4 \times 6^1$). Using SAS statistical analysis software and the macros described by Kuhfeld (2010), an efficient fractional factorial experimental design was created with 48 alternative combinations of the attributes. An efficient design size with 48 alternatives was developed with 1 status quo and 2 non-status quo alternatives per choice set, and four choice sets arranged in six survey blocks. Respondents were randomly assigned a questionnaire with one of the six versions of the questionnaire.

Choice Set 1

Attribute		Expected outcomes over 10 years		
		Strategy A	Current Strategy	Strategy B
Homes powered with wood in my state		30,000 homes	20,000 homes	10,000 homes
Unhealthy air days in my community		5 days per year	10 days per year	30 days per year
Large wildfires in my state		12 large wildfires per year	12 large wildfires per year	9 large wildfires per year
Forest health in my state		60% healthy forests	20% healthy forests	20% healthy forests
My household's monthly energy bill		\$200 (\$2,400 annually)	\$100 (\$1,200 annually)	\$120 (\$1,440 annually)
I would choose (select one only)		☐	☐	☐

Figure 5.1. Example of a choice set used in the questionnaire.

The 16-page survey instrument contained four sections. Section 1 provided a short introduction and collected information about respondent residence and opinions about energy generation, public land management, and climate change. Section 2 provided background information about energy consumption in the US, forest restoration treatments, and details about what woody biomass energy is, how it is generated, sustainable levels of production from public forests in Montana, and the costs and benefits associated with biomass harvesting and energy generation from biomass. Section 3 defined the attributes and presented the respondent with one block of four choice sets. Respondents were reminded to consider their budget constraints and alternative uses of their income. An example choice set is provided in Figure 5.1. Section 4 collected information about the respondents' experience with the survey and sociodemographic information, which allowed comparison between the collected sample and the general population of the state.

A mixed-mode data collection strategy was employed to obtain a stratified random sample of the population of Montana. Respondents were contacted with an invitation letter mailed to their home explaining the purpose of the research and presenting one of the following response options: (a) a web address and unique identification (ID) number that served as a password to complete the survey online, (b) a notification that they would soon be receiving a physical survey packet in the mail, or (c) both a web address with ID number *and* the option to wait and receive a physical copy of the questionnaire in the mail if they did not respond online. Individuals in the online-only group (a) who had not completed the survey after about two weeks received a reminder post-card in the mail. Individuals in the other two survey groups (b and c) were contacted using the four-contact method described in Dillman (2007), which is designed to maximize response rate and minimize non-response bias.

The sample was stratified according to two criteria to ensure coverage of people who live in forested areas and people who live in airsheds with a history of poor air quality. Residents of forested areas were identified using US EPA level III Ecoregions (EPA 2013). Poor air-quality airsheds were identified as EPA non-attainment airsheds, which have failed to meet national ambient air quality standards (EPA 2013). Residents of forested ecoregions were expected to have stronger preferences toward the WILDFIRES and FORESTS attributes because of their proximity to forestland. Residents of non-attainment airsheds were expected to have stronger preferences toward the AIRDAYS attribute because of their higher levels of experience with poor air quality. Contrary to expectations, preliminary testing of an airshed variable did not produce significant interactions with any of the attributes and was omitted from the final models.

5.4. Econometric Model

The theoretical foundations of the MNL are random utility maximization (Mcfadden 1973) and the characteristics theory of value (Lancaster 1966). Random utility explains that the utility associated with a particular alternative from a choice set is composed of both an observable and a random component,

$$U_j = V(x_j, p_j;\ \beta) + \varepsilon_j \tag{5.1}$$

where U_j is the true but unobservable utility associated with the consumption of profile *j*, *V* is the systematic indirect utility function, x_j is a vector of the attribute levels associated with profile *j*, p_j is the cost of profile *j*, β is a vector of preference parameters, and ε_j is a random error term. An individual will only select alternative *i* over alternative *j* if the utility associated with alternative *i* is greater than the utility from alternative *j.*

Assuming the errors in the regression can be described by a Gumbel distribution and are independently and identically distributed, the probability that an individual will select alternative *i* over alternative *j*, can be expressed as

$$P(i|C) = \frac{\exp(\mu V_i)}{\sum \exp(\mu V_{j)}} \tag{5.2}$$

where μ is a scale parameter inversely proportional to the variance of the error term. By assuming constant error variance, this parameter can be set to equal one (Ben-Akiva and Lerman 1985).

Two MNL specifications were examined in this study. The first model contained only the choice attributes, represented by equation (5.3). Preferences are assumed to be homogeneous across respondents, which may not hold true because there are individual characteristics that are likely to explain some portion of the preferences that people have toward environmental goods. The second model specification, represented by equation (5.4), was expanded to include socioeconomic and attitudinal characteristics of respondents to account for preference heterogeneity, and squared versions of the attributes to account for non-linearity in relationships between the attribute levels and likelihood of selecting a particular alternative.

$$P_n(i|C_n) = \frac{exp(\beta_{ni}X_{ni} + \alpha C_n + \tau Q_{ni})}{\sum exp(\beta_{nj}X_{nj}\ \alpha C_n + \tau Q_{nj})} \tag{5.3}$$

$$P_n(i|C_n) = \frac{exp(\beta_{ni}X_{ni} + \lambda_{ni}X^2{}_{ni} + \alpha C_n + \tau Q_{ni} + \gamma R_n X_i + \theta R_n C_n)}{\sum exp(\beta_{nj}X_{nj} + \lambda_{nj}X^2{}_{nj} + \alpha C_n + \tau Q_{nj} + \gamma R_{nj} + \theta R_n C_n)} \tag{5.4}$$

X_{ni} is a vector of terms for the attribute levels encountered by individual n; β_{ni} is a vector of associated estimated coefficients; $X^2{}_{ni}$ is a vector of squared attribute levels, with associated coefficient λ_{ni}; C_n is the cost attribute associated with each alternative and α is the associated coefficient; Q_{ni} is an alternative specific constant (ASC), taking a value of 1 for status quo alternatives and zero otherwise, with an associated coefficient of τ; R_n is a vector of case-specific socioeconomic characteristics that is interacted with the alternative-specific attribute-level variables, and has an associated coefficient of γ; and i and j are as previously defined. The coefficients were estimated using maximum likelihood estimation. Tables 5.1 and 5.2 provide descriptions of all the variables used in the models.

The ASC accounts for variation in choice that is not explained by changes in choice attribute levels, average monthly energy bill, or socioeconomic characteristics. Sometimes referred to as "status quo bias", this phenomenon results in decision-makers selecting the status quo at a rate higher than would be predicted by an economic model of consumer decision making (Samuelson and Zeckhauser 1988). This paper uses the more neutral term "status quo effect" (SQE) to avoid the suggestion that this phenomenon is the result of conscious bias on the part of the respondent or is the result of a statistically biased estimator. There are numerous rational and psychological explanations for the presence of the

SQE (Adamowicz et al. 1998, Boxall et al. 2009). Failing to account for the SQE can result in model estimates that overstate the effect of changes in attributes on respondent choices (Samuelson and Zeckhauser 1988).

In order to obtain policy relevant interpretations of the estimated coefficients, the marginal effects of each attribute must be calculated. Based on the models represented by equations (5.3) and (5.4) for attributes 1 through *K,* the average household marginal willingness to pay (MWTP) for a one-unit improvement in the *kth* attribute can be estimated by equations (5) and (6), respectively

$$\frac{\beta_n}{\alpha} \tag{5.5}$$

$$\left(\frac{\beta_n+\sum_{m=1}^{M} \gamma_{nm} G_m + 2\lambda \mathrm{X}}{\alpha+\sum_{m=1}^{M} \theta_{nm} G_m}\right) \tag{5.6}$$

where *G* represents the fraction of the population in Montana that falls into each of the *m* socioeconomic or attitudinal categories (as reported in Table 5.2), λ is the coefficient of the squared attribute level, *X* is the attribute level at which MWTP is being estimated, and all other parameters are defined as above. Based on the method used by Han et al. (2008), equation (5.6) produces adjusted average household MWTP that corrects for the potential that survey respondents were not representative of the demographic characteristics of the study area as a whole.

Table 5.2. Sociodemographic and attitudinal variables with Montana and survey sample means

Variable	Definition	Montana (%)	Sample (%)
SKEPTIC	dummy variable =1 for individuals who do not believe in man-made climate change	54.0[a]	50.7
HIGHINC	dummy variable =1 for households with annual income > $100k	15.3[b]	18.9
COLLEGE	dummy variable =1 for individuals with at least a bachelor's degree	28.7[b]	49.8
SENIOR	dummy variable =1 for individuals who are 65 years old or older	16.0[b]	39.5
FORESTED	dummy variable=1 for households located within a forested ecoregion	55.6[c]	56.1

Sources: a. Yale Project on Climate Change Communication (2014)
b. Census Bureau (2010a)

c. Census Bureau (2010b)

5.5. Results

The survey yielded 540 total responses for the state of Montana, of which 488 contained completed choice sets and were included in the data analysis. An additional eight respondents were excluded from the analysis under the assumption that they did not account for budget constraints. These respondents reported household income of less than $25,000 per year and selected profiles with the highest level of energy bill ($400/month), which represents almost 20% of their income. For each survey mode, the number of responses and the response rate are provided in Table 5.3. Internet only was characterized by a poor response rate (5.9%), with mail only and mixed mode resulting in 54.1% and 49.7% response rates, respectively. Survey respondents were, on average, older, better educated, and wealthier than residents of the state as a whole (Table 5.2).

Preliminary questions in the survey revealed respondents have an interest in issues related to the attributes in the choice sets. For example, 88% of respondents agreed that public forests are in need of restoration, to conserve biodiversity, reduce risk of large wildfires, or minimize the impacts of insect and disease infestation. Respondents expressed concerns related to air quality, with 63% of respondents indicating that smoke from wildfires and the burning of slash piles negatively affected the health of people in their community, and 57% of people agreeing that air pollution from cars, industry, power plants and wood stoves negatively affected the health of people in their community.

Respondents were less enthusiastic about woody biomass energy in relation to other energy options, ranking it 6th in preference out of ten options when asked to rank their top three sources of household energy. Hydroelectric was the most popular energy option. Solar (2nd), wind (3rd), natural gas (4th), and geothermal energy (5th) also received more support than woody biomass energy. Woody biomass energy was ranked ahead of nuclear energy (7th), coal (8th), oil (9th), and crop biomass (10th).

However, responses to questions about biomass harvest and energy generation revealed generally positive attitudes. For example, a majority of respondents (74%) indicated that they supported higher amounts of woody biomass harvest from public lands to generate energy. Respondents also indicated that they would support biomass energy facilities in their community. Support was higher for small scale biomass energy facilities like ones used to heat schools (76%), than large-scale woody biomass energy facilities that put electricity onto the power grid (61%). In response questions about disposition toward paying a premium for renewable or local energy, less than half (45%) of respondents indicated that they would voluntarily pay higher monthly energy bills for renewable energy, while only 42% indicated that they would be willing to pay higher energy bills for energy that is produced locally.

Table 5.3. Survey Response Rates

Survey Mode	Sent invitations	Delivered invitations	Responses	Response rate
Internet-only	5,433	5,059	300	5.9%
Mail-only	174	159	86	54.1%
Mixed-mode	343	310	154	49.7%

Table 5.4 presents the parameter estimates of the two models. It was expected that increases in the level of HOMES and FORESTS would be associated with increased likelihood of an alternative being selected because higher levels of both attributes are benefits. Increases in AIRDAYS, WILDFIRES, and BILL, on the other hand, make the respondent worse off and are expected to decrease the likelihood of an alternative being selected. The coefficients in the base model are all statistically significant at less than the 1% level (α=0.01) and their signs are consistent with expectations. The positive coefficient on the ASC in the base model is statistically significant, suggesting a significant SQE.

In the full model, the coefficients on choice attributes represent the preferences of base-case respondents. Here, the base case represents non-high income earners, who are not seniors, have less than a bachelor’s degree in education, do not live in a forested eco-region, and do believe that humans are causing climate change through the burning of fossil fuels. All of the attribute coefficients in the full model have the expected sign and all but the WILDFIRES coefficient were statistically significant at better than a 1% level. Coefficients for *HOMES_SQ*, *FORESTS_SQ*, and *AIRDAYS_SQ* reveal statistically significant diminishing marginal effects of changes in the levels of the attributes on the probability of choosing a particular alternative. As in the base model, the full model has a positive and significant ASC, indicating that respondents had a preference for the status quo option, regardless of the change in the levels of the attributes.

Table 5.4. Regression Analysis Results

	Base Model		Full Model	
	Coefficient	Std. Err.	Coefficient	Std. Err.
HOMES	0.0110***	0.00263	0.0526***	0.0155
AIRDAYS	-0.0436***	0.00486	-0.0844***	0.0246
WILDFIRES	-0.0417***	0.0128	-0.0457	0.115
FORESTS	0.0335***	0.00194	0.159***	0.0141
BILL	-0.00625***	0.000547	-0.00669***	0.000571
ASC	0.345***	0.0675	0.293***	0.109
SKEPTIC X HOMES			-0.0138***	0.00516
SKEPTIC X AIRDAYS			0.0338***	0.0107
SKEPTIC X WILDFIRES			0.0273	0.0252
SKEPTIC X FORESTS			-0.0157***	0.00394
HIGHINC X HOMES			0.0120*	0.00655
HIGHINC X AIRDAYS			-0.000662	0.0127
HIGHINC X WILDFIRES			-0.0188	0.0348
HIGHINC X FORESTS			0.00445	0.00537
COLLEGE X HOMES			0.00186	0.00529
COLLEGE X AIRDAYS			-0.0232**	0.0106
COLLEGE X WILDFIRES			-0.00198	0.0263
COLLEGE X FORESTS			0.00309	0.00411
SENIOR X HOMES			-0.0101*	0.00535
SENIOR X AIRDAYS			0.00279	0.0107
SENIOR X WILDFIRES			-0.0670**	0.0271
SENIOR X FORESTS			-0.00536	0.00407
FORESTED X HOMES			0.00339	0.00531
FORESTED X AIRDAYS			-0.00433	0.0104
FORESTED X WILDFIRES			-0.0427*	0.0259
FORESTED X FORESTS			0.00448	0.00395
HOMES_SQ			-0.000574**	0.000226
AIRDAYS_SQ			0.000961*	0.000561
WILDFIRES_SQ			0.00154	0.00510
FORESTS_SQ			-0.00155***	0.000173

N	5805	5709
log pseudolikelihood	-1799	-1673
likelihood ratio test[b]		p>chi2 = 0.000

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
[b]: Null hypothesis of likelihood ratio test is joint insignificance of variables

The negative coefficients on *SKEPTIC X HOMES* and *SKEPTIC X FORESTS,* and the positive coefficient on *SKEPTIC X AIRDAYS*, reveal that respondents who don't believe that humans are causing climate change have a statistically significantly lower WTP for these attributes than respondents who do believe in man-made climate change. The positive and significant coefficient on *HIGHINC X HOMES* reveals that high-income respondents have a higher WTP for homes powered with wood. The negative and significant coefficient on *COLLEGE X AIRDAYS* suggests that respondents with at least a bachelor's degree are less likely than others to select a strategy where the number of AIRDAYS increased relative to the status quo. Significant negative coefficients on *SENIOR* X *HOMES* and *SENIOR* X WILDFIRES reveal that respondents who were older than age 65 were less willing to pay for increases in the number of homes powered with wood in the state, and were more sensitive than others to increases in the number of large wildfires. *FORESTED X WILDFIRES* is positive and significant at the 10% level, suggesting that respondents who live in a forested eco-region have a higher WTP to avoid increases in the number of large wildfires.[8]

5.5.1 Social Willingness to Pay

Table 5.5 reports the average monthly household MWTP for the base model and the full model, estimated using equations (5) and (6), respectively. A 95% confidence interval for each value was estimated with 500 bootstrap iterations using the method described by Efron and Tibshirani (1986). The confidence intervals highlight that all average MWTP estimates, except WILDFIRES in the full model, are

[8] In Montana, many high value homes have been built in forested areas with high amenity values. To ensure that living in a forested ecoregion was not acting as a proxy for high income, the correlation between the two variables was tested and no significant correlation was found.

statistically significantly different from zero. The MWTP estimates from the full model are the focus of the remainder of the paper.

Table 5.5. Household Marginal Willingness to Pay for Attributes per month

Attribute	Marginal Unit	Base Model			Full Model		
		Average household MWTP ($)	95% confidence interval ($)		Average household MWTP ($)	95% confidence interval ($)	
HOMES	1000 homes	1.79	0.89	2.68	3.75	1.96	5.55
AIRDAYS	1 day/year	-6.98	-8.90	-5.06	-8.43	-11.65	-5.22
WILDFIRES	1 wildfire/year	-6.68	-10.47	-2.90	-4.78	-4.88	0.68
FORESTS	1 percentage point	5.36	4.30	6.41	13.74	10.55	16.94
ASC	na	56.69	32.47	80.90	43.89	8.58	79.19

The MWTP of the attributes can facilitate estimation of the economic impacts of changes in the levels of provision of individual attributes. However, because the attributes are measured in different units, MWTP cannot easily be used to compare the relative magnitude of the marginal effects between attributes. One way to interpret the values that facilitates more direct comparison between the attributes is to estimate WTP for a particular percent change in each of the attributes. Using results from the full model, Table 5.6 provides the annual household MWTP for each attribute, the aggregate MWTP across the 405,525 households in the state (Census Bureau 2010a), and the aggregate WTP for a 10% improvement in each of the attributes. Viewed through this lens, WTP for improvements in forest health is significantly larger than the other attributes, with an aggregate WTP of $134 million annually to increase the level of healthy forests by 2 percentage points in the next ten years. WTP to for a 10% improvement in *AIRDAYS* is second largest in magnitude at $41 million annually. To provide some context with which to interpret these aggregate MWTPs, the total annual household expenditure on energy bills in Montana was about $414 million in 2011.[9]

[9] The Average household energy bill Montana in 2011 was $84.97 per month (EIA 2011).

Table 5.6. Aggregate Annual Marginal Willingness to Pay

Attribute	Annual Household MWTP	Aggregate MWTP ($)	10% improvement from status quo	WTP for 10% improvement from status quo ($)
HOMES	45.00	18,248,625	2,000 homes	36,497,250
AIRDAYS	-101.16	41,022,909	1 day	41,022,909
WILDFIRES[a]	-57.36	23,260,914	1.2 wildfires	27,913,097
FORESTS	164.88	66,862,962	2 percentage points	133,725,924
ASC	526.68	213,581,907	na	na

[a]: WTP estimates for WILDFIRES are not statistically significantly different from zero.

Montana residents are willing to pay $36 million per year for a 10% increase in the number of homes powered with woody biomass, which equals an additional 2,000 homes with an average annual aggregate energy requirement of 21 million kWh.[10] Therefore a program that increases the number of homes powered with wood by 10% is economically efficient if the costs to supply the energy do not exceed $36 million annually, or $1.74 kWh^{-1}. When compared to the average residential electricity rate in Montana of around $0.10 per kWh^{-1} (EIA 2011), and the levelized cost of producing biomass energy, also at $0.10 kWh^{-1}, a rate of $1.74 kWh^{-1} appears high [11]. However, the rate of $1.74 kWh^{-1} corresponds to the aggregate amount that the entire population of the state is willing to pay for the additional woody biomass energy, not the amount that individual households are willing to pay for electricity from woody biomass in their own energy bill. The high aggregate MWTP for woody biomass energy relative to the cost of production is likely due to the public good aspects of woody biomass energy, which include the mitigation of climate change through fossil fuel offsets by renewable energy, as well as the potential to facilitate restoration treatments in public forests.

[10] The Average household energy consumption in Montana in 2010 was 10.5 MWh per year (EIA 2011).
[11] The levelized cost of electricity represents the cost per unit energy produced of building and operating an energy plant (EIA 2015).

5.6. Discussion

Montanans are willing to pay for woody biomass energy produced using biomass from public forests, as well as for the broader environmental benefits of resource management, namely improved forest health, better air quality and reduced frequency of large wildfires, although MWTP for the latter was not statistically significant. Priority ordering of the attributes is challenging because of differences in units of marginal change between the attributes; however, the results do suggest forest health is more important to residents than the other attributes considered in this study. In this section, the MWTP estimates of the attributes are compared with published WTP estimates for similar resources in North America, and the implications of findings from this survey for woody biomass energy generation are discussed.

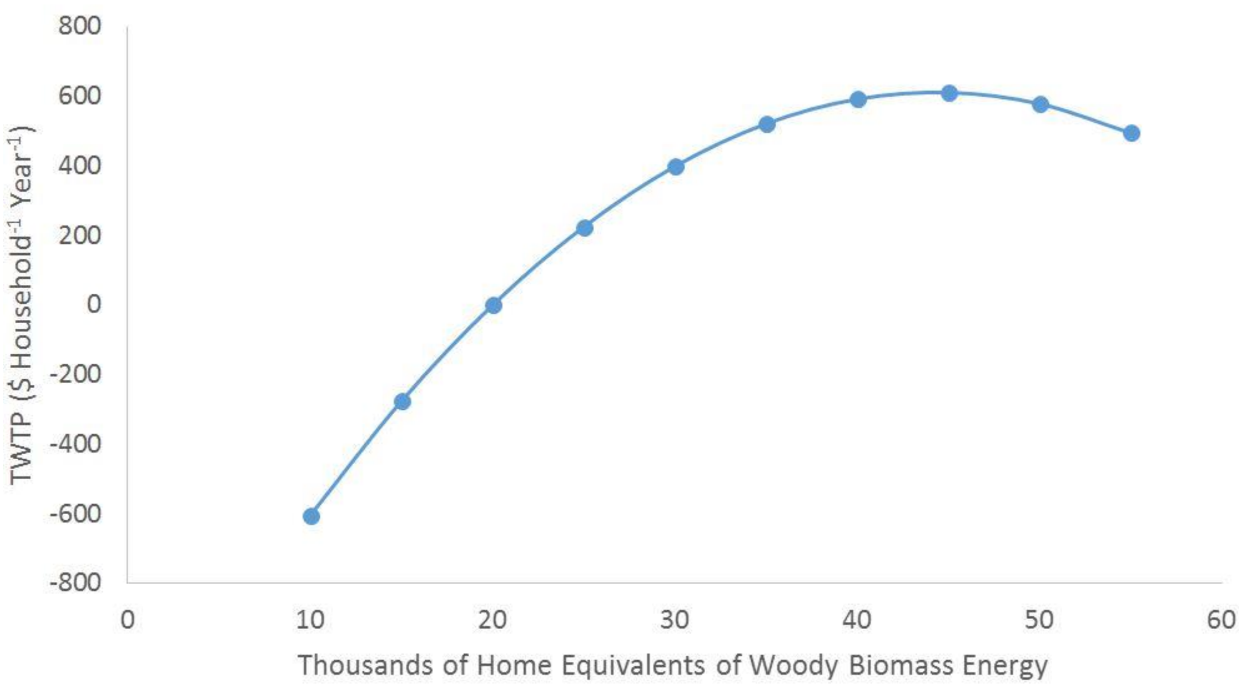

Figure 5.2. Total Willingness to Pay for Woody Biomass Energy Generation

The large MWTP for improvements in forest health and biodiversity conservation are consistent with other estimates from the Western US found in the literature (Garber-Yonts et al. 2003, Loomis et al. 2005, Mueller 2013, O'Donnell et al. 2014). Positive MWTP to avoid exposure to degraded air quality is also consistent with other estimates in the literature (Dickie and Messman 2004, Rittmaster et al. 2006, Rittmaster et al. 2008, O'Donnell et al. 2014).

The statistical insignificance of MWTP to reduce the number of large wildfires in Montana was unexpected. Previous studies have found significant WTP for fuels treatments that reduce the probability of wildfire burning one's own private property (Kim and Wells 2005, Kaval et al. 2007, Kaval 2009). However, in these studies, respondents were expressing WTP for direct benefits to themselves in terms of reduced burn probabilities around their homes. When surveys are distributed beyond households who will directly benefit from reduced risk of private property loss, diminished WTP has been found. O'Donnell et al. (2014) found statistically significant but small MWTP of Montanans to avoid home evacuations due to wildfire, and provided a discussion on the economic rationale of residents' WTP decisions based on the expected value of their losses due to wildfire. In light of other findings, the statistically insignificant MWTP to avoid large wildfires in the state is not unrealistic, given the fact that the majority of Montana residents do not reside in wildfire prone areas and it is the preferences of residents of the entire state that were investigated. In this case, respondents were revealing their WTP for a good that is mostly public in nature, rather than for direct benefits to themselves. The higher WTP for WILDFIRES exhibited by respondents in forested ecoregions is consistent with the hypothesis that WTP to avoid large wildfires is driven by direct benefits of reducing the risk to one's own private property.

The MWTP of \$3.75 per month per household (\$45 annually) for an additional 1000 homes powered with wood is equal to a price premium of \$0.0043 MWh^{-1}, over and above the current price of energy in Montana. This is equal to a 3.7% increase in annual household energy bills. The magnitude of this estimate appears small compared to the value found by Susaeta et al. (2011), who estimated a MWTP of \$0.049 kWh^{-1} for electricity produced with woody biomass in Florida, Arkansas, and Virginia. However, their estimate represents the total willingness to pay (TWTP) for the woody biomass energy, while the estimate in this study represents the amount that residents would be willing to pay over and above the current price they pay for energy. In addition, the Susaeta et al. (2011) estimate includes values for multiple positive environmental externalities associated with woody biomass energy generation (i.e. CO2 reduction from offsetting fossil fuel consumption, and forest heath improvements and wildfire risk reduction associated with increased forest restoration treatments), which were estimated separately in this study.

Montanans are willing to pay higher energy bills to substitute some fossil fuel energy consumed in the state with woody biomass energy generated from feedstock harvested on public lands. This does suggest residents value the public good aspects of woody biomass energy. However, a critical question for public forest policy-makers and managers is 'how much woody biomass harvesting on public lands is economically efficient'? The economically efficient level of woody biomass energy production from public forests in Montana will be where the economic surplus is maximized. That is, where marginal benefits equal marginal costs.

For the purpose of policy analysis, we accept the estimates of aggregate MWTP from this study as the marginal benefit of a program to increase the level of woody biomass energy generated from Montana's public forests. TWTP for alternative levels of woody biomass energy generation was estimated through summing bootstrapped aggregate MWTP for 10,000 to 55,000 home equivalents, in increments of 5,000 homes. As illustrated in Figure 5.2, TWTP starts to decrease (aggregate MWTP becomes negative) from about 45,000 homes powered with wood. That is, residents' demand for woody biomass energy from public forests is quickly satiated. Since the marginal costs of woody biomass energy generation are not zero, the economically efficient level of energy generation from public forestland in Montana must be less than 45,000 household equivalents.

About 10.5 tons of forest residues, on a dry weight basis, are required to produce the annual electricity requirements for an average Montanan household[12]. This can be harvested as part of a restoration treatment from about 0.7 ha of public forest[13]. Thus, an additional 700 ha of forest would need to be treated annually to supply the equivalent of 1,000 more households with woody biomass energy, assuming a total of 21,000 households. An additional 14,000 ha would need to be treated annually to supply the equivalent of 20,000 more households with woody biomass energy. This represents treatment on an additional 0.04% to 0.8% of the Montanan public forest estate annually.

The survey data support several complementary explanations for the relatively low demand for woody biomass energy generated from public land. First, Montanans' consider woody biomass energy as an inferior good; natural gas and all forms of renewable energy except crop biomass were preferred to woody biomass as a source of household energy. Second, although respondents indicated generally positive attitudes toward utilizing residues from public forests for energy generation (74% indicated that they support more utilization of residues from public forests for energy generation), respondents ranked timber harvesting 7th out of 9 possible uses for public forests. Therefore, if timber harvest is viewed as being in conflict with other more highly ranked goods and services provided by public forests, support for woody biomass energy will be diminished. Third, when asked to indicate the degree to which the

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[12] In a commercial-scale power generation facility (10+ MW output of electricity), 1 ton of woody biomass fuel will produce 10,000 pounds of steam, which will generate 1 MWh of electricity (USFS 2007). Therefore it takes about 1 dry ton of biomass for each of the 10.5 MWh of energy consumed annually by the average household in Montana (EIA 2011).

[13] There are 9.5 million acres of timberland in need of treatment and 188 million tons of removable biomass on those acres (Rummer et al. 2005). Residues make up 30% of that biomass, so there are 56.4 million tons of removable residues (Perlack and Stokes 2011). Removable residues divided by treatable acres yields 6 tons of residues per acre, or 6 tons per 0.4 hectare. Therefore, 0.7 ha yields 10.5 tons of biomass.

various attributes affected their decisions in the choice sets, the percent of respondents who indicated a high or very high level of concern about forest health (65%), wildfires (56%), energy bill (54%), and air quality (46%), all significantly outweighed the desire for more woody biomass energy (24%). Fourth, half of the state's population does not believe in man-made climate change, thus diminishing the perceived public good value of woody biomass energy.

5.7. Conclusions

The US has committed to reducing carbon emission from the energy sector to 30% below 2005 levels by 2030, necessitating a shift away from fossil fuels in the nation's energy portfolio (EPA 2015). There is a need to quantify the externalities associated with alternative sources of energy generation in order to make socioeconomically efficient decisions about how to supply the country's energy needs. This study investigated social preferences toward woody biomass energy in order to quantify the nonmarket costs and benefits associated with it and comment on the socioeconomic efficiency of the energy source. The use of the choice modelling method facilitated the simultaneous estimation of separate values for multiple attributes associated with woody biomass harvest and energy generation. The estimated MWTP values can be used by policy makers and public land managers to determine to what degree the social benefits of utilizing the residues from forest restoration or fuel treatment programs to generate energy offset the costs associated with the programs.

The low and rapidly diminishing MWTP to generate woody biomass energy from public forests in Montana has potential forest management and energy policy implications at the national level. The main conclusion arising from this research is that Montanans do not support public forestland management at a level more than double the current level of woody biomass harvested for energy generation. Further research is necessary to determine whether the preferences of Montanans' for woody biomass energy generated from public forests are applicable more generally throughout the

United States. There is also a need for future research to examine whether woody biomass sourced from private forest land may be more acceptable to the public.

5.8 Chapter 5 References

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Chapter 6

Heterogeneity in Preferences for Woody Biomass Energy in the US Mountain West

Abstract:

This paper investigates social preferences for the generation of energy with woody biomass produced by restoration treatments on public forests in Arizona, Colorado and Montana, USA. Both multinomial logit and latent class logit (LCL) models are fit to data generated with a choice modeling survey and used to produce estimates of marginal willingness to pay (MWTP) for the attributes representing the number of homes powered with woody biomass energy, number of large wildfires, percentage of healthy forests, and local air quality. Sociodemographic and attitudinal characteristics of respondents are used to account for heterogeneity in preferences for the attributes. Based on statistical measures of goodness of fit, the LCL is found to provide the best fit of the data. Model results reveal positive mean MWTP for all attributes in the survey. However, four distinct classes of respondents are identified with distinct preferences, revealing conflicting views of woody biomass energy generation.

6.1. Introduction

The United States has passed legislation aimed at reducing greenhouse gas emissions (United States Congress 2005, United States Congress 2007, EPA 2015). In order to achieve the goals set by these commitments, significant amounts of fossil fuel energy will need to be replaced with renewable energy. There are multiple renewable technologies from which to choose, and each option has associated costs and benefits. In order to maximize the social benefits from investments in renewable energy technologies, the external costs and benefits must be quantified and included in the decision making process.

One option for increasing renewable energy production is woody biomass, which can be used to produce electricity, thermal energy, or liquid biofuels. Woody biomass is already used to produce about 2% of the energy in the United States (EIA 2010) and has the potential to supply up to 10% (Zerbe 2006). The high cost of production relative to fossil fuels has been a major barrier to expansion of woody biomass energy in the US (Gan and Smith 2006). However, there are external effects that are not captured in markets which can affect the socioeconomic efficiency of woody biomass energy relative to other energy options. Because these effects are not captured in markets, nonmarket valuation techniques are needed to quantify the value that society has for them.

Throughout the Western United States there are large areas of public forest that are departed from historic conditions as a result of past management decisions that include wildfire exclusion, poor timber harvesting practices, and over-grazing (Wienk et al. 2004, Hutto 2008).These overgrown and structurally homogenous forests are less resilient to natural and manmade disturbances, less able to support a variety of native plant and animal communities (Huntzinger 2003, Hiers et al. 2007), and are more likely to experience unusually severe and damaging wildfires (Schwilk et al. 2009) that can threaten numerous human and ecological values (Graham et al. 2004). Forests that are departed from historic fire regimes have increased tree density, structural homogenization, and fuels buildup (Taylor 2004). These conditions are typically mitigated using mechanized thinning treatments, prescribed fire, or a combination of the two (Rummer et al. 2005). Mechanized thinning treatments use heavy equipment to remove and process excess fuels, sometimes generating merchantable forest products like sawlogs, pulpwood and woody biomass. In this paper, woody biomass is defined as the limbs, tops, needles, leaves, and other parts of trees and woody plants that are generated as the byproducts of forest management.

The purpose of this paper is to quantify public willingness to pay (WTP) for an increase in the production of woody biomass energy from public forestland and the potential environmental and socioeconomic effects associated with it. This has been performed for a study area consisting of the Rocky Mountain States of Arizona, Colorado, and Montana.

Together the states have 26 million hectares of forestland, across all ownerships, with 7.5 million hectares classified as moderately or severely departed from natural fire regimes (Rummer et al. 2005). Treatment of departed hectares to improve forest health or reduce wildfire risk would produce substantial amounts of woody biomass feedstock that could potentially be used for energy generation. There are however, potential negative effects associated with woody biomass harvest, including reduced forest health through reduced soil productivity (Thiffault et al. 2011). Additionally, emissions from the woody biomass energy facilities may reduce air quality in communities where they are located (Chum et al. 2011). In order to assess the socioeconomic efficiency of any management action that would increase the amount of woody biomass harvested from public forests, public preferences toward the potential outcomes need to be quantified. Woody biomass energy has many supporters, but is not without opposition and the debate about sustainability and climate change implications is ongoing.

Public preferences are quantified in this study using a choice experiment and econometric modeling techniques that allow sources of preference heterogeneity to be identified and accounted for. A choice experiment is well suited to this task because it provides the ability to quantify preferences toward multiple separate effects associated with an increase in woody biomass energy, in terms of WTP and willingness to make trade-offs between the different effects.

The paper proceeds with a review of studies that have used nonmarket valuation to analyze preferences toward renewable energy, followed by a description of the development of the survey instrument. The econometric models used to analyze the data are presented next, followed by the results of the study, and finally, the study's findings and implications.

6.2. Public Preference for Renewable Energy

Nonmarket valuation studies have been used to quantify the value of a wide range of environmental goods and services associated with renewable energy generation, including reduced greenhouse gas emissions (Roe et al. 2001, Longo et al. 2008, Solomon and Johnson 2009, Susaeta et al. 2011, Solino et al. 2012), improved air quality (Roe et al. 2001, Bergmann et al. 2006), preservation of landscape quality (Álvarez-Farizo and Hanley 2002, Bergmann et al. 2006), reduced wildfire risk (Bergmann et al. 2006, Solino et al. 2012) and preservation of wildlife habitat and biodiversity (Álvarez-Farizo and Hanley 2002, Bergmann et al. 2006). Positive WTP has also been found for non-environmental attributes including energy security (Longo et al. 2008, Li et al. 2009) and rural employment (Solino et al. 2012).

Few studies to date have attempted to value externalities associated with woody biomass energy generation specifically. Susaeta et al. (2010) used a choice modeling exercise to assess preferences toward externalities associated with woody biomass energy in Arkansas, Florida, and Virginia. Respondents had positive (but statistically insignificant) WTP for improved forest health, reductions in CO_2 emissions and improvement of forest habitat from reduced wildfire risk. Because almost 90% of forest lands in the Southern US are privately owned, little of the woody biomass described by Susaeta et al. (2011) study would come from public lands. In the absence of financial incentives, including markets for carbon, applications of the findings of this study to inform and influence private forest management and woody biomass energy generation appear limited. Solino et al. (2012) found positive WTP in Spain for reduced greenhouse gas emissions, reduced risk of forest fire and reduced pressure on natural resources associated with the utilization of woody biomass for electricity generation.

Data sets from choice experiments are often analyzed using a multinomial logit model (MNL), which assumes that preferences are homogeneous across the population. However, studies have commonly found heterogeneity in preferences that can be explained by geographic location, environmental attitudes, political viewpoints and sociodemographic characteristics. Significant predictors of preference heterogeneity have been found to include age (Ek 2005, Bergmann et al. 2008, Longo et al. 2008), gender (Solomon and Johnson 2009, Susaeta et al. 2010), education (Bergmann et al. 2008, Susaeta et al. 2010), income level (Álvarez-Farizo and Hanley 2002, Ek 2005, Bergmann et al. 2006), and urban vs. rural place of residence (Bergmann et al. 2008), and environmental attitudes (Álvarez-Farizo and Hanley 2002, Longo et al. 2008), including climate change beliefs (Solomon and Johnson 2009). Generally, younger, more educated, and higher income people are more likely to support renewable energy production and have higher WTP.

Failure to account for preference heterogeneity with the use of a MNL can lead to biased estimates of WTP and an inability to consider distributional effects across different classes of the population (Boxall and Adamowicz 2002). The simplest and most commonly used approach to relaxing the assumption of homogeneous preferences is to include interaction terms between individual-specific characteristics and choice attributes in a MNL. This approach does nothing to relax the potentially unrealistic assumptions of Independence of Irrelevant Alternatives (IIA) and uncorrelated unobserved error over time (Yoo and Ready 2014). Two models exist which relax not only the assumption of homogeneous preferences, but also of IIA and uncorrelated error terms. One is the random parameter logit model (RPL), which accounts for heterogeneity assuming that preference parameters are randomly distributed across the population and allows model parameters to vary randomly across individuals (Train 1998). The second is the latent class model (LCL), which assumes that multiple distinct classes exist in the population, between which preferences vary, but within which preferences are homogenous. The latent class model accounts for preference heterogeneity by simultaneously estimating class membership and choice parameters based on individual characteristics (Boxall and Adamowicz 2002). The ability to identify distinct groups of individuals with like preferences is a useful tool for identifying distributional impacts of policy change.

Multiple studies have used LCL, RPL, or both to examine preferences for renewable energy. Susaeta et al. (2011) found evidence of heterogeneity in preferences toward woody biomass energy, using both MNL with interactions and RPL, in the eastern US. Bergman et al. (2008) used RPL to account for heterogeneity in preferences for renewable energy generation arising from differences between urban and rural residents in Scotland. Strazzera et al. (2012) used LCL in an analysis of preferences toward visual impacts of wind farms in Spain, finding that groups with distinct preferences could be defined by psychometric variables. Yoo and Ready (2014) used multiple model specifications (LCL, RPL, and a RPL-LCL hybrid) in an investigation of preferences toward multiple sources of renewable energy in

Pennsylvania. Cicia et al. (2012) used LCL in their analysis of preferences toward multiple renewable energy sources in Spain and found that three distinct groups existed in the population that could be defined by both their strength of preference toward different renewable energies, as well as sociodemographic characteristics.

In addition to accounting for preference heterogeneity, the latent class framework can be used to address issues of attribute non-attendance (ANA), in which respondents ignore one or more of the attributes when making their choices (Scarpa et al. 2009, Campbell et al. 2011, Yoo and Ready 2014). Non-attendance can range from ignoring a single attribute, up to complete non-attendance, in which all attributes are ignored and alternatives are selected randomly. ANA result from respondents simply ignoring attributes that are not relevant to them, or as a result of respondents using heuristics to reduce the cognitive effort required when faced with complex choice tasks (Hensher 2006). In choice experiments, it is assumed that respondents consider the levels of all attributes and weigh the tradeoffs that exist between alternatives in a choice set (Scarpa et al. 2009). If respondents ignore an attribute for reasons other than deriving zero utility from it, their behavior is inconsistent with random utility theory. Therefore, these behaviors can have consequences that include biased estimates and the inability to accurately estimate trade-offs between attributes (Scarpa et al. 2009).

To our knowledge, no other studies have analyzed social preferences for woody biomass energy in the Western US, or toward biomass harvest exclusively from public forestland. In addition this is the first study to not only account for heterogeneity in preferences for woody biomass energy, but also utilize the LCL model to identify distinct groups of preference that exist for woody biomass energy.

6.3. Methods

6.3.1 Choice Experiment Survey

In order to determine which socioeconomic and environmental effects associated with woody biomass energy generation are most important to residents of the study area, focus group meetings were held in Missoula, MT, Denver, CO, and Flagstaff, AZ, between July and September of 2013. The meetings were attended by stakeholders from the United States Forest Service (USFS), state agencies, universities, the forest industry, wildlife and land conservation groups, and local recreation groups.[14] The five most important attributes associated with woody biomass energy identified at the meetings were: homes powered with wood in the state (abbreviated HOMES); unhealthy air days experienced locally (AIRDAYS); large wildfires in the state (WILDFIRES); forest health in the state (FORESTS); and household monthly energy bill (BILL).[15] Each attribute was defined over a ten-year time horizon to provide a realistic time-frame in which to adopt and implement new forest management strategies, while also remaining relevant to respondents. The attributes are defined together with their status quo and alternative levels in Table 6.1.

Table 6.1. Definitions of choice attributes

Variable	Definition	Levels	Units
HOMES	The amount of woody biomass energy produced annually. Defined as electric or thermal energy produced using residues from restoration treatments on public forests.	10000, 20000*, 30000, 50000	Homes per year
AIRDAYS	The number of days per year when air quality is unhealthy for sensitive groups in your community.	5, 10*, 15, 30	Days per year
WILDFIRES	The number of wildfires per year that burn at least 1000 acres and threaten homes and watersheds.	6, 9, 12*, 15	Wildfires per year
FORESTS	The percent of healthy forestland, across all forest ownership categories.	10, 20*, 30, 60	Percent

[14] Representatives from tribal forestry, private forest owners, and environmental groups with a strong anti-biomass energy stance were contacted about attending the meetings, but were either unavailable or uninterested in attending the meeting.
[15] A sixth attribute, “Rural Job Creation” was ranked as important and initially included in the survey, but was dropped after peer-review suggested that the survey was overly-complex. “Rural Job Creation” was dropped, rather than one of the attributes, because the economic value of job creation can be estimated from markets, while the other attributes are not presently traded in markets.

BILL	Household average monthly energy bill in US dollars.	80, 100*, 120, 150, 200, 400	US dollars

* indicates status quo attribute level

HOMES was used as the metric for biomass energy production based on feedback from focus group participants. It was determined that the number of homes powered would be more easily interpreted than a unit of electric or thermal generation, such as kilowatt hours (KWh) or British thermal units (Btus). The woody biomass energy produced was defined as replacing energy that is currently produced using fossil fuels, and the ability to offset fossil fuel use and reduce long-term impacts of climate change was presented as a benefit associated with HOMES.

AIRDAYS was based on the average number of days from 2008 through 2012 that air quality was documented as “unhealthy for sensitive groups” at United States Environmental Protection Agency (EPA) monitoring stations throughout the study area, representing the average number of days the average household is exposed to levels of air pollutant concentrations that are high enough to pose a health risk to older adults, young children and people with specific health concerns (EPA 2013). Consistent with findings by Pope et al. (2009), the definition explained that long-term exposure to the concentrations of particulate matter present when air quality is “unhealthy for sensitive groups” may pose health risks to all members of the community and reduce life expectancy.

The WILDFIRES status quo level was determined using a GIS and spatial data from the Monitoring Trends in Burn Severity project (MTBS 2012). The definition highlighted the average number of homes destroyed annually over the past decade in each study state, but also stressed that the majority of homes were destroyed by a small number of very destructive fires, that the number of fires each year is highly variable, and that wildfires are an important beneficial natural disturbance present in healthy forest ecosystems.

The FORESTS definition emphasized the fact that healthy forests support a greater diversity of native plant and animal species and are more resilient to disturbances. The proportion of healthy forests in each study state was determined using the Vegetation Condition Class classification system, which categorizes the level of departure of current vegetation conditions from a historic reference (Barrett et al. 2010). This proportion includes all forested lands across all ownerships.

The average monthly household energy bill (BILL) for study area states was used to define the status quo of the cost attribute (EIA 2011). This bill includes both electricity and natural gas, and other fuel for heat. Energy bill is an obligatory payment mechanism that is less likely to induce protest responses than a government tax or fee. The annual equivalent of BILL was also provided in the choice sets to decrease the likelihood of respondents interpreting the monthly amounts as inconsequential.

Although the status quo levels for each attribute varied between the three study states, they were similar enough that a single status quo level that was realistic across all three states could be used for each of the attributes. Having a single status quo level ensured that the data from all three study states could be pooled into a single dataset.

There are 1,536 possible combinations of the attributes and their levels (4^4 x 6^1). Using SAS software (SAS Institute Inc. 2015), and the macros described by Kuhfeld (2010), an efficient fractional factorial experimental design was created with 48 alternative combinations of the attributes. Four choice sets were arranged in six survey blocks with 1 status quo and 2 non-status quo alternatives per choice set. Respondents were randomly assigned a questionnaire with one of the six survey blocks.

The 16-page survey instrument contained four sections. Section 1 provided a short introduction and collected information about respondent residence and opinions about energy generation, public land management, and climate change. Section 2 provided background information about energy consumption in the US, forest restoration treatments, and details about what woody biomass energy is, how it is generated, sustainable levels of production from public forests, and the costs and benefits associated with biomass harvesting and energy generation from biomass. Section 3 defined the attributes and presented the respondent with the choice sets. Respondents were reminded to consider their budget constraints and alternative uses of their income. Section 4 collected information about the respondents' experience with the survey and sociodemographic information, which allowed comparison between the collected sample and the general population of the state.

A mixed-mode data collection strategy was employed to obtain a stratified random sample of the study population. Respondents were contacted with an invitation letter mailed to their home explaining the purpose of the research and presenting one of the following response options: (a) a web address and unique identification (ID) number that served as a password to complete the survey online; (b) a notification that they would soon be receiving a physical survey packet in the mail, or (c) both a web address with ID number *and* the option to wait and receive a physical copy of the questionnaire in the mail if they did not respond online. Individuals in the online-only group, (a), who had not completed the survey after about two weeks received a reminder post-card in the mail. Individuals in the other two survey groups (b and c) were contacted using the four-contact method described in Dillman (2007), which is designed to maximize response rate and minimize non-response bias. The sample was stratified to ensure coverage of people who live in forested areas and people who live in airsheds with a history of poor air quality. Residents of forested areas were identified using US EPA level III Ecoregions (EPA 2013). Poor air-quality airsheds were identified as EPA non-attainment airsheds: airsheds that have failed to meet national ambient air quality standards (EPA 2013). Because of the large number of Spanish speaking residents in Arizona and Colorado, for census tracts with at least 50% Hispanic population, respondents were provided with the option to complete the Spanish language version of the survey.

Residents of forested ecoregions were expected to have stronger preferences toward the WILDFIRES and FORESTS attributes because of their closer proximity to the location of the effects associated with these attributes. Residents of non-attainment airsheds were expected to have stronger preferences toward the AIRDAYS attribute because of their higher levels of experience with poor air quality. Contrary to expectations, preliminary testing of the airshed variable did not produce significant interactions with any of the attributes and was omitted from the final models.

6.3.2 Econometric Model

Two econometric models were fitted to the data. The first is the multinomial logit model (MNL), which is the most commonly used model for CM data. The theoretical foundations of the MNL are random utility maximization (Mcfadden 1973) and the characteristics theory of value (Lancaster 1966). Random utility explains that the utility associated with a particular alternative from a choice set is composed of both an observable and a random component,

$$U_j = V(x_j, p_j;\ \beta) + \varepsilon_j \tag{6.1}$$

where U_j is the true but unobservable utility associated with the consumption of profile *j*, *V* is the systematic indirect utility function, x_j is a vector of the attribute levels associated with profile *j*, p_j is the cost of profile *j*, β is a vector of preference parameters, and ε_j is a random error term. An individual will only select alternative *i* over alternative *j* if the utility associated with alternative *i* is greater than the utility from alternative *j.*

Assuming the errors in the regression can be described by a Gumbel distribution and are independently and identically distributed, the probability that an individual will select alternative *i* over alternative *j*, can be expressed as

$$P(i|C) = \frac{\exp(\mu V_i)}{\sum \exp(\mu V_{j})} \tag{6.2}$$

where μ is a scale parameter inversely proportional to the variance of the error term. By assuming constant error variance, this parameter can be set to equal one (Ben-Akiva and Lerman 1985). This can be expanded and expressed as

$$P_n(i|C_n) = \frac{exp(\beta_{ni}X_{ni} + \tau Q_{ni})}{\sum exp(\beta_{nj}X_{nj} + \tau Q_{nj})} \tag{6.3}$$

where X_{ni} is a vector of terms for the attribute levels encountered by individual n; β_{ni} is a vector of associated estimated coefficients; Q_{ni} is an alternative specific constant (ASC), taking a value of 1 for status quo alternatives and zero otherwise, with an associated coefficient of τ.

In the model represented by equation (6.3), preferences are assumed to be homogeneous across respondents, which may not hold true because there are individual characteristics that are likely to explain some portion of the preferences that people have toward environmental goods. This assumption can be relaxed through the inclusion of individual-specific characteristics, R, that are interacted with the alternative-specific attribute-levels.

$$P_n(i|C_n) = \frac{exp(\beta_{ni}X_{ni} + \tau Q_{ni} + \gamma R_n X_i)}{\sum exp(\beta_{nj}X_{nj} + \tau Q_{nj} + \gamma R_{nj})} \tag{6.4}$$

Table 6.2. Sociodemographic and Attitudinal Characteristics

Variable	Definition	Sample (%)	Study Population (%) [a]
HIGHINC	Dummy variable =1 if household annual income > \$100k	25.9	21.5 [b]
COLLEGE	Dummy variable =1 if have at least a bachelor's degree	59.0	31.2 [b]
SKEPTIC	Dummy variable = 1 if do not believe in anthropogenic climate change	47.6	49.2 [c]
FORESTED	Dummy variable =1 if live in a forested ecoregion	53.6	N/A
AIRQUALITY	Dummy variable =1 if think that smoke and other air pollution negatively impacts community	23.2	N/A
RESTORATION	Dummy variable =1 if think that public forests are in need of restoration treatments	89.8	N/A
CONFUSED	Dummy variable =1 if think that the survey was confusing	27.3	N/A

Notes:
a: Based on the weighted average of the populations of Arizona, Colorado, and Montana.

b: Source: Census Bureau (2010a)
c: Source: Yale Project on Climate Change Communication (2014)

The second model used to examine reference heterogeneity in this paper is a variation of the MNL, called latent class (LCL) model, which provides the ability to identify subsets of the population with similarities in preference structures. The LCL framework assumes that individuals are members of a group that has particular preferences, independent from the choice problem being analyzed (Swait 1994). Preferences differ across groups, but are homogeneous within groups. Given *S* classes in the population and individual *n* belonging to class *s(s = 1,…,S),* the indirect utility function can be written as:

$$U_{in|s} = \beta_s X_{in} + \varepsilon_{in|s} \qquad (6.5)$$

where β_s is the vector of preference parameters for class *s*, X_{in} is a vector of individual and alternative specific characteristics and $\varepsilon_{in|s}$ represents the random component of utility for individual *n* of class *s*. The probability of individual *n* selecting alternative *i* is now partially dependent on what class of the population the respondent belongs to, with preference parameters varying by class:

$$P_{n|s}(i) = \frac{exp(\beta_s X_i)}{\sum_{n=1}^{N} exp(\beta_s X_k)} \qquad (6.6)$$

Inclusion in a particular class is defined by socioeconomic, demographic and attitudinal characteristics hypothesized to affect preferences. As outlined by Holmes and Adamowicz (2003), identification of class membership is accomplished through the following logit model:

$$P_{ns} = \frac{exp\ (\lambda_s Z_n)}{\sum_{s=1}^{S} exp(\lambda_s Z_n)} \qquad (6.7)$$

Where *Z* is a set of individual characteristics and λ is a vector of parameters. Selection of the number of classes can be informed by the Bayesian information criterion (BIC) and Akaike information criterion (AIC) (Swait 1994). *A priori* assumptions about the underlying elements of preference heterogeneity and the practical explanatory interpretation of the classes can be taken into account.

The joint probability of individual *n* belonging to class *s* and selecting alternative *i* can also be defined as the expected value of the product of the probabilities defined in equations (6) and (7),

$$P_n(i) = \sum_{s=1}^{S}\left[P_{n\,|\,s}(i)P_{ns}\right] = \sum_{s=1}^{S}\left(\frac{\exp(\lambda_s Z_n)}{\sum_{s=1}\exp(\lambda_s Z_n)}\right) * \prod_{k=1}^{K}\left(\frac{\exp(X_{ink}\beta_s)}{\sum_{j=n}\exp(X_{ink}\beta_s)}\right) \tag{6.8}$$

where k = 1,…K are the choice sets presented to individual *i*.

In order to obtain policy relevant interpretations of the estimated coefficients, the marginal effects of each attribute must be calculated. Based on the models represented by equations (6.3) and (6.4)*,* the average household marginal willingness to pay (MWTP) for a one-unit improvement in any attribute can be estimated by equations (6.9) and (6.10), respectively

$$-\frac{\beta_{n\,\widehat{attribute}}}{\beta_{n\,\widehat{cost}}} \tag{6.9}$$

$$-\left(\frac{\beta_{n\,\widehat{attribute}}+\sum_{m=1}^{M}\gamma_{nm}G_m}{\beta_{n\,\widehat{cost}}+\sum_{m=1}^{M}\theta_{nm}G_m}\right) \tag{6.10}$$

where *G* represents the fraction of the study area population that falls into each of the *m* socioeconomic or attitudinal categories accommodated in equation (6.3), (as reported in Table 6.3), and all other parameters are defined as above. Based on the method used by Han et al. (2008), equation (6.10) produces adjusted average household MWTP that corrects for the potential that survey respondents were not representative of the demographic characteristics of the study area as a whole.

From the estimated coefficients produced by equation (6.6), for each class 1 through S, MWTP for each attribute can be estimated as

$$-\left(\frac{\beta_{s\,\widehat{attribute}}}{\beta_{s\,\widehat{cost}}}\right). \tag{6.11}$$

In order to account for ANA within a latent class framework, parameters of some or all of the attributes can be restricted for certain classes. Restricting the parameter of an attribute to zero represents the attribute being ignored and having a marginal utility of zero. In this study, a class is estimated in which the parameters on all of the attributes are restricted to equal zero, to account for respondents who appeared to have ignored all attributes and made their choices randomly.

6.4. Survey Response

An equal number of surveys of each mode were sent to each of the three study states. The survey yielded 1,226 total complete responses. Response rates varied by contact mode and across the three study states. Response rates were 42% for the mail-only contact group, 39% for the mixed contact-mode, and 4.5% for the internet-only contact mode. Overall, response rates were highest in Montana and lowest in Arizona, resulting in 540 responses in MT, 404 responses in CO, and only 282 responses in AZ. Survey respondents were on average, better educated and more likely to have a household income at least $100,000 per year than the population as a whole.

Table 6.3. Response Rates by Mode

	Internet	Mail	Mixed
Invitations sent	16,775	511	1,019
Undeliverable invitations	1,451	57	125
Delivered invitations	15,324	454	894
Complete responses	692	189	345[a]
Overall response rate	**4.5%**	**42%**	**39%**
MT response rate	5.9%	54%	50%
CO response rate	4.5%	35%	36%
AZ response rate	3.1%	35%	29%

Note: a: 291 mixed-mode responses were completed with mail hard-copy and 54 were completed on the internet.

Respondents were strongly in favor of restoration treatments in public forests, with almost 90% in support of forest restoration treatments. A majority (71%) of respondents were also in favor of utilizing more woody biomass from public forests for energy generation. When it comes to renewable energy production, 73% of respondents want to see more renewable energy production, but only 45%

indicated that they would pay higher energy bills for renewable energy. A small majority (52.4%) of respondents believe that the climate is changing and that it is being caused by human activities. This is very close to the percent of people in the study area population that believe in anthropogenic climate change. Responses to a preliminary question regarding preferences for preferred sources of household energy consumption revealed that respondents may view woody biomass as an inferior energy option when it comes to mitigating emissions leading to climate change. Woody biomass energy ranked 6th out of 10 options, behind hydroelectric, solar, wind, natural gas and geothermal when asked to rank their top three sources of household energy[16].

6.5. Results and Discussion

Three model specifications were estimated. Two variations of the MNL were estimated and their results are presented in Table 6.4. Results from the latent class specification are presented in Table 6.5. It was expected that increases in the level of HOMES and FORESTS would be associated with increased likelihood of an alternative being selected because higher levels of both attributes are benefits. Increases in AIRDAYS, WILDFIRES, and BILL, on the other hand, make the respondent worse off and are expected to decrease the likelihood of an alternative being selected.

6.5.1. MNL and MNL Interaction Results

Results for two MNL model specifications are presented in Table 6.4. The base specification of the MNL utilizes only the attribute levels and the ASC to explain the alternatives selected by respondents in the choice sets. The coefficients in the MNL model are all statistically significant at better than a 1% level (α=0.01) and their signs are consistent with expectations. The positive coefficient on the ASC in the base model is statistically significant, suggesting a significant SQE.

The MNL interactions model incorporates individual-specific sociodemographic and attitudinal

[16] Woody biomass ranked ahead of nuclear, coal, oil, and crop biomass.

information, described in Table 6.2, to account for preference heterogeneity. In this model, the coefficients on choice attributes represent the preferences of base-case respondents. Here, the base case represents respondents who believe in climate change, are not high income earners, do not have a college degree, do not live within a forested ecoregion, and do not think poor air quality negatively affects their community. In the MNL interactions model, HOMES and WILDFIRES are statistically insignificant, and HOMES does not have the expected sign. AIRDAYS, FORESTS and BILL are all statistically significant and have the expected signs. As in the basic MNL, the interactions model has a positive and significant ASC, indicating that respondents had a preference for the status quo option, regardless of the change in the levels of the attributes.

Coefficients on the interaction terms describe the effects that these characteristics have on preferences for each attribute. The significant negative coefficient on COLLEGE X BILL indicates that people with a college education are more sensitive to increases in BILL than respondents without a college education. This may be a result of these respondents better accounting for their budget constraints. Although they have a higher sensitivity to BILL, the significant positive coefficient on COLLEGE X FORESTS and the significant negative coefficient on COLLEGE X AIRDAYS indicate that college graduates have higher WTP than others for FORESTS and AIRDAYS. The significant negative coefficient on SKEPTIC X BILL indicates that people who do not believe in climate change are more sensitive to increases in BILL than others. The significant negative coefficient on SKEPTIC X FORESTS and the significant positive coefficient on SKEPTIC X AIRDAYS indicate that these people also have lower WTP for FORESTS and AIRDAYS.

The positive and significant coefficient on AIRQUALITY X AIRDAYS suggests that people who think that their community is negatively affected by poor air quality actually have lower WTP to avoid increases in poor air quality days than respondents who do not think poor air quality affects their community. People who live in forested areas have stronger preferences for avoiding increases in the number of large wildfires, as indicated by the significant negative coefficient on FORESTED X WILDFIRES. The interactions produced with the forest restoration opinion variable show that people who think that public forests are in need of restoration have higher WTP for HOMES and FORESTS.

Table 6. 4. MNL Regression Results

	Base MNL		MNL Interactions	
	Coefficient	Std. Err.	Coefficient	Std. Err.
HOMES	0.00796***	0.00169	-0.00582	0.00643
AIRDAYS	-0.0461***	0.00341	-0.0484***	0.0142
WILDFIRES	-0.0356***	0.00837	-0.0191	0.0323
FORESTS	0.0316***	0.00131	0.0156***	0.00474
BILL	-0.00533***	0.000329	-0.00454***	0.00146
ASC	0.307***	0.0435	0.314***	0.0449
SKEPTIC X HOMES			-0.00496	0.00315
SKEPTIC X AIRDAYS			0.0167**	0.00730
SKEPTIC X WILDFIRES			0.0139	0.0174
SKEPTIC X FORESTS			-0.0113***	0.00267
SKEPTIC X BILL			-0.00207***	0.000717
HIGHINC X HOMES			0.00485	0.00360
HIGHINC X AIRDAYS			-0.00921	0.00891
HIGHINC X WILDFIRES			-0.0250	0.0199
HIGHINC X FORESTS			0.00499	0.00320
HIGHINC X BILL			0.000364	0.000793
COLLEGE X HOMES			0.00320	0.00332
COLLEGE X AIRDAYS			-0.0265***	0.00720
COLLEGE X WILDFIRES			0.000292	0.0175
COLLEGE X FORESTS			0.00797***	0.00269
COLLEGE X BILL			-0.00134*	0.000727
FORESTED X HOMES			0.00479	0.00310
FORESTED X AIRDAYS			-0.00270	0.00698
FORESTED X WILDFIRES			-0.0284*	0.0167
FORESTED X FORESTS			0.00407	0.00258
FORESTED X BILL			0.000385	0.000684
AIRQUALITY X HOMES			-0.00464	0.00377
AIRQUALITY X AIRDAYS			0.0154**	0.00773
AIRQUALITY X WILDFIRES			0.0157	0.0196
AIRQUALITY X FORESTS			0.00256	0.00299
AIRQUALITY X BILL			0.000888	0.000825
RESTORATION X HOMES			0.0132**	0.00555
RESTORATION X AIRDAYS			0.00779	0.0123
RESTORATION X WILDFIRES			-0.00822	0.0286
RESTORATION X FORESTS			0.0151***	0.00411
RESTORATION X BILL			0.000292	0.00124
Log-likelihood	-4135.7		-3997.5	

AIC	8283.5	8067.2
BIC	8328.4	8336.0
N	13116	12933

Standard errors in second column
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

6.5.2 Latent Class Model

The LCL model was specified using all of the variables that appear in MNL interactions model. Model specifications ranging from two to six classes were run and a four-class model was selected as the best specification based on AIC and BIC. The need for a restricted class was recognized when the sign on BILL was positive and significant in one of the classes in earlier iterations of the LCL model, suggesting a class of respondents were ignoring the cost associated with each alternative, or selecting alternatives with higher cost, all else constant. Multiple levels of ANA and various numbers of restricted classes were explored. The specification with a single class representing complete ANA was found to best fit the data. Consequently, class 4 in the final model specification represents complete ANA, with all attribute parameters restricted to zero. In an attempt to explain the behavior of the ANA class, the variable CONFUSED, defined in Table 6.3, was added to the model.

As shown in Table 6.5, with the exception of the coefficient on HOMES for class 1, all coefficients for all choice attributes are statistically significant and have the expected sign, for all classes. All classes have reserved their lowest MWTP for HOMES. MWTP with 95% confidence intervals were estimated for each class using the delta method (Hole 2007), and are presented in Table 6.6.

Table 6.5. Latent Class Model Results

	Class 1 (Reference)		Class 2		Class 3		Class 4 (Constrained)	
	Woody Biomass Skeptics		Woody Biomass Believers		Low WTP		Attribute Non-Attenders	
Marginal utilities	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.	Coefficient	Std. Err.
HOMES	-0.00109	0.00371	0.0637***	0.0120	0.0437***	0.00968		
AIRDAYS	-0.0264***	0.00891	-0.312***	0.0409	-0.143***	0.0264		
WILDFIRES	-0.0540***	0.0200	-0.166***	0.0489	-0.326***	0.0536		
FORESTS	0.0473***	0.00642	0.0760***	0.00771	0.0836***	0.0140		
BILL	-0.00365***	0.000650	-0.0120***	0.00164	-0.0696***	0.00940		
ASC	-0.547***	0.131	1.121***	0.221	1.173***	0.226	1.050**	0.455
Class membership parameters								
SKEPTIC			0.218	0.285	1.097***	0.245	1.002***	0.314
HIGHINC			0.131	0.244	-0.561**	0.285	-0.926**	0.417
COLLEGE			0.816***	0.274	-0.0887	0.238	-0.159	0.374
FORESTED			0.0390	0.235	-0.451**	0.226	-0.729**	0.303
AIRQUALITY			-1.111**	0.443	-0.0424	0.263	-0.226	0.381
RESTORATION			-0.760*	0.423	-1.268***	0.399	-1.498***	0.478
CONFUSED			-0.184	0.295	0.00551	0.255	0.627**	0.312
Constant			-0.165	0.524	0.589	0.497	0.620	0.811
Posterior membership probability	35.7%		24.1%		23.0%		17.2%	
Log-likelihood	-3786.4							
AIC	7668.7							
BIC	8027.2							
N	12933							

Class 1 is the reference class and represents the largest share of respondents with 36%. Determinants of class membership for the other classes are interpreted with respect to class 1. Members of class 1 are woody biomass energy skeptics. They are the most concerned about anthropogenic climate change and the need for forest health restoration treatments. They have a strong preference for change in status quo management of public forests (negative ASC); however, they are also the class that is least interested in generating energy from woody biomass. This suggests members of class 1 support active management to restore forest health, but view woody biomass energy as an inferior renewable energy alternative for addressing their concerns about climate change.

Table 6.6. Household Marginal Willingness to Pay per Month, by Class

Attribute	Woody Biomass Skeptics (Class 1)			Woody Biomass Believers (Class 2)			Low WTP (Class 3)		
	Mean MWTP	95% CI		Mean MWTP	95% CI		Mean MWTP	95% CI	
HOMES	-0.30	-2.28	1.69	5.31	3.17	7.46	0.63	0.40	0.85
AIRDAYS	-7.22	-13.50	-0.94	-26.01	-32.87	-19.15	-2.05	-2.52	-1.57
WILDFIRES	-14.76	-27.84	-1.68	-13.85	-22.55	-5.15	-4.68	-5.79	-3.57
FORESTS	12.93	6.86	19.00	6.34	4.74	7.94	1.20	0.99	1.42
ASC	-149.68	-227.56	-71.80	93.55	51.64	135.45	16.85	11.10	22.60

Note: MWTP for class 4 is constrained to zero for all attributes

Class 2 is the second largest of the classes, representing 24% of respondents. They are woody biomass energy believers. Members of class 2 are highly educated and were least confused about the survey. They have statistically significantly higher mean MWTP for HOMES and AIRDAYS than any other class. The fact that class 2 has the highest mean MWTP for AIRDAYS, while also being the least likely to feel that their community is negatively affected by poor air quality, conforms with the positive coefficient on AIRQUALITY X AIRDAYS in the MNL interactions model. It seems that people who live in communities with better air quality are less willing to accept reduced air quality than people who live in communities with poorer air quality to begin with.

Classes 3 and 4 have similar class membership parameters and together account for 40% of respondents. They are characterized as having low or zero MWTP for all attributes. Relative to classes 1 and 2, they are statistically significantly less likely to believe in anthropogenic climate change, have high income, or live in a forested ecoregion. They are also statistically significantly less likely to believe forests are in need of restoration treatments relative to class 1. They are also less likely to have a college education, although not significantly so. The attributes in the survey instrument did not resonate with members of classes 3 and 4. These people are skeptical about climate change and do not live in forested ecoregions, so forest health, wildfire risk and woody biomass energy appear to be less relevant to them than for members of classes 1 and 2.

What distinguishes classes 3 and 4 from each other is that members of class 3 do report small MWTP for all choice attributes (MWTPs for class 4 members are not statistically significantly different from zero), and members of class 4 are statistically significantly more likely to be confused by the survey than the members any other class. The parameter coefficients for all attributes for class 4 are constrained to zero, representing respondents making random choices with no regard to the levels of the attributes in the alternatives. The significantly higher likelihood for members of class 4 to have felt that the survey was confusing suggests that the apparently random choices made by these respondents is due, at least in part, to confusion or lack of willingness to invest the cognitive effort required by the survey.

Constraining WTP estimates for class 4 to zero is justified under either of two potential explanations for the non-attendance. First, because the constraints on class 4 represent complete ANA, it may be that none of the attributes are relevant to the respondent and the WTP for these respondents is truly zero. Second, if the non-attendance is related to cognitive burden and the use of heuristics, as suggested by the higher levels of confusion for this class, then although the true WTP for these respondents may be greater than zero, the respondents did not express their true preferences and welfare estimates will be biased by their inclusion in the analysis. Without certainty about their true preferences, the most conservative approach is to constrain WTP for all attributes to zero for the 17.2% of respondents represented by class 4.

6.5.3 Aggregate Willingness to Pay and Model Comparison

According to three measures of goodness of fit (log-likelihood, AIC, and BIC), the LCL model provides a better fit to the data than the MNL models. Welfare estimates from the LCL are considered to be more accurate because of the model's ability to account for both preference heterogeneity and attribute non-attendance. The MNL interactions model accounts only for preference heterogeneity.

Mean MWTP values from the LCL have been calculated as the sum of the mean MWTP from each group, multiplied by the respective membership probability, with class-specific estimates that are not statistically different from zero included as zero. Because these are simply a weighted average of the class-specific mean MWTP estimates, no confidence interval was obtained. These estimates are provided in Table 6.7, along with estimates derived from the MNL interactions model. Even with 17.2% of the sample constrained to a mean MWTP of zero for all attributes, the LCL produced higher mean estimates for AIRDAYS, and WILDIRES. Mean MWTP for HOMES and FORESTS are higher in the MNL interaction model. However, mean MWTP for HOMES is not statistically different from zero in the MNL interactions model.

Table 6.7. Average Monthly Household MWTP

Attribute	Marginal Unit	LCL Mean [a]		MNL interaction [b]		
		Average household MWTP ($)	95% confidence interval ($)	Average household MWTP ($)	95% confidence interval ($)	
HOMES	1000 homes per state	1.43	na	1.66	-0.16	3.48
AIRDAYS	1 day/year	-9.32	na	-6.96	-11.18	-2.74
WILDFIRES	1 wildfire/year in each state	-9.98	na	-8.88	-17.67	-0.11
FORESTS	1 percentage point in each state	6.42	na	8.21	4.57	11.84
ASC	na	-27.01	na	69.11	4.11	134.11

Notes:
a: Mean MWTP for LCL model is calculated as the sum of the MWTP from each group, multiplied by the respective membership probability. Class-specific estimates that are not statistically different from zero were included as zero.

b: MWTP estimates with 95% confidence intervals for the MNL interaction models were estimated with 500 bootstrap iterations using the method describe by Efron and Tibshirani (1986).

Because of the differing units used to define them, it is difficult to directly compare the magnitudes of the MWTP estimates across attributes. However, calculating WTP for a ten percent change in each attribute can facilitate a more direct comparison. As shown in Table 6.8, mean annual household MWTP for each attribute is aggregated for the 4.75 million households in the study area (Census Bureau 2010a). This is then multiplied by the number of units in a 10% change from the status quo. According to this metric, WTP for improved forest health is the largest amongst all of the attributes, at little over $732 million annually. This is followed by aggregate annual WTP for WILDFIRES and AIRDAYS at $663 million and $531 million, respectively. Viewed through this lens, it is clear that WTP for HOMES is substantially smaller than the other attributes, at $163 million annually.

Table 6.8. Aggregate Annual Marginal Willingness to Pay, from LCL Model

Attribute	Annual Household MWTP	Aggregate MWTP ($)	10% improvement from status quo in each state	WTP for 10% improvement from status quo ($)
HOMES	17.10	81,260,980	2,000 homes	162,521,959
AIRDAYS	-111.81	-531,475,361	1 day	-531,475,361
WILDFIRES	-116.20	-552,359,161	1.2 wildfires	-662,830,993
FORESTS	77.04	366,199,469	2 percentage points	732,398,938
ASC	-324.18	-1,540,942,291	na	na

6.6. Conclusion

The primary goal of this study is to quantify the preferences that residents of Arizona, Colorado and Montana have towards the utilization of woody biomass harvested from public forests for energy generation and associated potential environmental effects. MNL and LCL models were fitted to the data. According to measures of statistical goodness of fit, the LCL provides the best fit of the data. In addition to accounting for preference heterogeneity, the LCL model allowed a constrained class to be estimated which accounted for attribute non-attendance behavior by some respondents. This accounts for a potential source of bias that is not addressed in the MNL models.

Results reveal positive mean WTP for increased energy generation with woody biomass from public forests, improvements in forests health, avoided large wildfire, and avoided days of degraded air quality. However, preferences are not homogeneous across the population. Sociodemographic characteristics and environmental attitudes are significant predictors of preferences toward increased woody biomass harvest from public forests, the utilization of the biomass to produce energy, and the environmental externalities that may be associated with changes in public forest management.

The findings of this study have important policy implications for the social acceptance of utilizing woody biomass from public forests in the Mountain West for energy generation. The analysis highlights that there is controversy surrounding woody biomass energy. Results from the LCL reveal that while there are 2 classes of people that are concerned about climate change, only one of the classes accepts woody biomass energy as a potential solution.

Given the size of the woody biomass skeptics class, it is unlikely that public forests could be managed for more woody biomass energy without conflict or considerable work toward collaboration among groups with disparate positions. The member of the biomass skeptics class have a high level of interest in public forest land management and the potential effects associated with woody biomass energy. The concerns of this class may be related to sustainability of woody biomass harvest. For example, 27% of respondents indicated that their answers on the choice sets were highly motivated by concerns that increased woody biomass energy will lead to more logging. Therefore, if biomass energy can be shown to have a positive ecological influence on public forestland, the views of biomass skeptics may become more positive toward woody biomass energy. This suggests the need for increased efforts to educate the public about potential benefits of woody biomass energy.

The low WTP and attribute non-attendance classes appear to be somewhat disengaged on the issue of public forestland management for energy due to a combination of beliefs about climate change and geography. Given their low level of concern for the attributes in this study, the low WTP and non-attendance classes will be challenging to target with outreach campaigns designed to inform people of the characteristics and potential benefits of woody biomass energy.

6.7 Chapter 6 References

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Chapter 7

Comparison of Survey Modes for Choice Modelling Survey Implementation

Abstract:

The cost-effectiveness of internet, mail only and mixed internet and mail survey modes was examined with a case study of woody biomass energy generation preferences of residents of Montana, Colorado and Arizona, using a choice modeling survey. Results reveal the internet survey mode to be the most cost effective method of collecting a standard sample size of 400 responses. Sensitivity analysis is conducted and shows that the cost advantage of internet over the mail only and mixed survey modes increases as the target number of responses increases, as a result of low marginal costs associated with extending additional invitations. The internet mode is found to produce a sample of respondents that is younger, more likely to have a college degree, and more likely to have a household income of at least $100,000 per year, than the mail and mixed modes. However, the differences in characteristics of the collected sample do not result in significant differences in estimates of willingness to pay for attributes in the survey.

1. Introduction

Stated preference nonmarket valuation studies rely on obtaining responses to surveys that present hypothetical markets for environmental goods and services which are not traded in actual markets. Contacting potential respondents and providing them with a survey has traditionally been performed using in-person interviews, telephone interviews, or via mail contact. More recently, internet-based survey methods have emerged as a viable method for data collection and have been increasing rapidly in popularity. Internet-based surveys offer a number of advantages including reduced response time, the ability to provide large amounts of information to respondents, and low marginal cost per response relative to other survey modes (Berrens et al. 2003). However, as a relatively new method, questions still exist about the representative nature of internet surveys.

The purpose of this paper is to test whether an internet only survey can be a cost-effective alternative to mail-only and mixed mail and internet survey modes for nonmarket valuation, while also maintaining the ability to collect a representative sample and produce unbiased estimates of economic measures of interest, e.g. willingness to pay (WTP). This is achieved through an experiment conducted as part of a choice modeling exercise investigating public preferences for renewable woody biomass energy in the Mountain West region of the United States. The paper contributes to the literature by being the first to compare the cost effectiveness of mail and internet-based survey modes for a choice modeling survey.

The paper proceeds by first reviewing the environmental valuation literature that has compared internet-based surveys to other sample methods. Then the study area, survey design, survey distribution modes, and econometric model used are described. Next, the results of the comparison of the three survey modes are presented. Finally, the findings and their implications for practitioners are discussed.

2. Review of Previous Studies of Survey Modes

Choosing which survey mode to utilize for a stated preference study involves tradeoffs in terms of survey labor and materials costs, time to produce survey materials and receive responses, ability to provide information to respondents, and sources of potential bias, such as sample bias. As a result, the choice of survey mode can affect the ability to collect a target sample size, as well as the quality of responses (e.g. including precision, respondent certainty in responses, number of protest responses, and consistency in responses). Internet-based surveys offer an advantage over other survey modes in terms of low marginal survey costs, length of time required to receive responses, and ability to provide respondents with information, but there are concerns about their ability to draw a representative sample from the population. (Berrens et al. 2003).

The purpose of non-market valuation surveys is to produce estimates of economic value for nonmarket goods and services. Therefore, perhaps the most important effects of survey mode for practitioners are potential differences in magnitude or quality of valuation estimates. A possible reason that internet sampling may produce different estimates than other modes is that sociodemographic characteristics and preferences of people with access to internet may differ from the population at large (although this can potentially be corrected for with models that account for preference heterogeneity and weighting in the calculation of WTP). For more discussion of survey mode effects see Marta-Pedroso et al. (2007) and Bell et al. (2011).

Findings regarding the effect of survey mode on valuation estimates are mixed. Some studies found no significant differences between internet and other survey modes (Fleming and Bowden 2009, Olsen 2009, Covey et al. 2010, Lindhjem and Navrud 2011). Bell et al. (2011) and Mjelde et al. (2016) on the other hand, both found internet samples produce lower estimates of economic value than other survey modes. Olsen (2009) found lower estimation precision and certainty in choice (as measured through the variance of unobserved effects for variance, and responses to debriefing questions for certainty) from an internet sample than mail. However, they also found a lower rate of protest responses (from zero bidders who were identified as protest responders in debriefing questions) in the internet sample. Lindhjem and Navrud (2011a) found no evidence of difference in “don’t knows” and protest responses between internet and face-to-face interviews. Based on their review of multiple studies that compared WTP estimates from internet surveys with other modes, Lindhjem and Navrud (2011b) concluded that there is little evidence to suggest that responses obtained from internet surveys are of lower quality than other modes.

To the best of our knowledge, only one nonmarket valuation survey has compared the cost effectiveness of an internet-based survey to other survey modes. Fleming and Bowden (2009) conducted a travel cost survey using both an internet-based and a mail-based survey and found the internet-based survey to be more cost-effective in their collection of 640 responses.

Studies in other social science and medical survey research have generally found internet-based surveys to be more cost-effective than mail-based surveys (Weible and Wallace 1998, Cobanoglu et al. 2001). However, Schleyer and Forrest (2000) found that results tend to be dependent on sample size, with internet more cost-effective than mail only for target sample sizes greater than 275. Sinclair et al.

(2012), however, found that even with a large collected sample sizes mail contact was the most cost-effective survey mode. The low cost of mail contact for Sinclair et al. (2012) is likely due in part to their choice of a single contact with no follow up, which is significantly less expensive than multiple contacts used in the commonly employed in the Dillman (2007) four-contact method for mail-based surveys.

Generally, internet-based surveys have been found to generate lower response rates than other methods. Unsurprisingly, Marta-Pedroso et al. (2007) found higher response rates to in-person interviews (84%) than random contact internet (5.1%). Sinclair et al. (2012) found higher response rates for a mail-survey mode, compared to a random contact internet survey mode, with an internet response rates of 4.7% for a personalized approach with invitations addressed personally to respondents by name, 2.2% for a generic approach inviting “households” to participate, and 30.2% and 10.5% for personalized and generic mail surveys. Both Lindhjem and Navrud (2011) and MacDonald et al. (2010) found higher response rates for mail-contact than pre-recruited internet panels. The surprising result that an internet mode using panels of people who had already agreed to participate in surveys failed to achieve higher response rates than a mail mode relying on random contact, speaks to the challenges of achieving competitive response rate with internet survey modes. In the only published study we are aware of that found higher response rates from internet than mail, Olsen (2009) achieved a 63.6% response rate from a pre-recruited internet panel and 60.3% using a mail survey mode.

The low marginal cost associated with sending additional invitations once fixed costs of designing the internet-based survey have been incurred has been cited as a reason for the favorable cost effectiveness of internet surveys (Berrens et al. 2003).The cost of an additional email invitation is close to zero, and the cost of sending additional mail invitation is also low compared to an additional contact for a mail-based survey. As sample size increases, low marginal costs can overcome the relatively low response rates achieved by internet survey. As a result of relatively high fixed costs and low marginal costs, internet-based surveys are likely to become more cost effective than mail-based surveys as the target sample size increases.

Although a large and growing proportion of US households have access to the internet, the level of access differs between socioeconomic groups, with lower access amongst seniors, people with low educational attainment, low household income, and rural residents (Perrin and Duggan 2015). This raises the concern that internet-based surveys may exacerbate the issue that already exists with other survey modes; collecting samples that are wealthier and better educated than the population as a whole. If a representative sample cannot be collected, the preferences of the population may not be accurately estimated, and biased estimates of the economic values of interest may result. Published survey mode studies suggest that, on average, internet respondents tend to be younger, wealthier and better educated than mail and in-person interview respondents (Olsen 2009, MacDonald et al. 2010, Windle and Rolfe 2011). Mixed-mode sampling approaches (e.g. internet and mail sampling) have been suggested as a way to reach segments of the population that don't have access to the internet (Champ 2003).

3. Methods

3.1 Case Study: Choice Modeling Survey of Preferences for Woody Biomass Energy

The cost-effectiveness of internet, mail only and mixed internet and mail survey modes was examined with a case study of woody biomass energy generation preferences of residents of Montana, Colorado and Arizona, using a choice modeling survey. In order to determine which socioeconomic and environmental effects associated with woody biomass energy generation are most important to residents of the study area, focus group meetings were held in Missoula, MT, Denver, CO, and Flagstaff, AZ in July through September of 2013. The meetings were attended by stakeholders from the United States Forest Service (USFS), state agencies, universities, the forest industry, wildlife and land conservation groups, and local recreation groups. Representatives from tribal forestry, private forest owners, and environmental groups with a strong anti-biomass energy stance were contacted about attending the meeting, but were either unavailable or uninterested in attending the meeting. The five most important attributes associated with woody biomass energy identified at the meetings were: homes powered with wood in the state (abbreviated to HOMES); unhealthy air days experienced locally (AIRDAYS); large wildfires in the state (WILDFIRES); forest health in the state (FORESTS); and household monthly energy bill (BILL). Each attribute was defined over a ten-year time horizon to provide a realistic time-frame in which to adopt and implement new forest management strategies, while also remaining relevant to respondents. The attributes are defined together with their status quo and alternative levels in Table 1.

Table 1. Definitions of choice attributes and quadratic variables

Variable	Definition	Levels	Units
HOMES	The amount of electric or thermal energy produced from woody biomass produced annually in the state, using residues from restoration treatments on public forests.	10000, 20000*, 30000, 50000	Homes per year
AIRDAYS	The number of days per year when air quality is unhealthy for sensitive groups in your community.	5, 10*, 15, 30	Days per year
WILDFIRES	The number of wildfires per year that burn at least 1000 acres and threaten homes and watersheds in the state.	6, 9, 12*, 15	Wildfires per year
FORESTS	The percent of healthy forestland in the state, across all forest ownership categories.	10, 20*, 30, 60	Percent
BILL	Household average monthly energy bill in US dollars.	80, 100*, 120, 150, 200, 400	US dollars

* indicates status quo attribute level

3.2 Description of Survey Modes

Data collection was contracted to the Bureau of Business and Economic Research at the University of Montana (BBER). A sample of 18,305 household addresses was obtained and there was a stratified random assignment of survey modes to the stratified addresses. Out of the sample of addresses used, 16,775 were sent internet-only invitations, 1,019 were sent mixed-mode invitations, and 511 were sent mail-only invitations. The mixed survey mode was administered as a potential method to alleviate sampling effects associated with the internet-based survey, but did not produce a significantly improved sample of the population.

The study area was stratified by state, air quality and forest ecoregion. The sample was stratified to ensure coverage of people who live in forested areas and people who live in airsheds with a history of poor air quality because these characteristics were hypothesized to affect preferences toward the attributes of interest. Residents of forested areas were identified using US EPA level III Ecoregions (EPA 2013). Poor air-quality airsheds were identified as EPA non-attainment airsheds, which have failed to meet national ambient air quality standards (EPA 2013). Respondents were identified as either urban or rural based on the classification of metro and non-metro counties as defined by the US Economic Research Service (ERS 2015)[17]. Throughout the entire study area, 87% of people live in metro counties. Although the proportion of urban residents varied significantly between states, with only 35% of the population in Montana residing in metro counties, and 86% and 95% in metro counties in Colorado and Arizona (ERS 2013).

Respondents were contacted with an invitation letter mailed to their home explaining the purpose of the research and randomly presented with one of the following response options: (a) a web address and unique identification (ID) number that served as a password to complete the survey online, (b) a notification that they would soon be receiving a physical survey packet in the mail, or (c) both a web address with ID number *and* the option to wait and receive a physical copy of the questionnaire in the mail if they did not respond online. Individuals in the online-only group (a) who had not completed

[17] Metro counties are defined in two ways (1) core metro counties are ones that contain at least one densely-settled urban area with 50,000 or more people, and (2) outlying metro counties that are economically tied to the core counties, as defined by at least 25% of workers in the county commuting to a core county, or at least 25% of the employment in the county consists of workers commuting from a core metro county.

the survey after about two weeks received a reminder post-card in the mail. Individuals in the other two survey groups (b and c) were contacted using the four-contact method described in Dillman (2007). The second mailing included the survey, the third mailing about two weeks later was a reminder postcard, and, if a response had still not been received, the fourth and final mailing included a second hardcopy of the survey. Mixed-mode respondents did not receive the $2 bill incentive that the mail-only respondents received in the second mailing. Because of the large number of Spanish speaking residents in Arizona and Colorado, for census tracts with at least 50% Hispanic population, respondents were provided with the option of completing a Spanish language version of the survey.

3.3 Estimating Cost-Effectiveness

In order to allow a level cost comparison between the survey modes, a common 400 response target was used to generate the cost per-response for each survey mode. The 400 response target was selected to represent a commonly pursued sample size in choice modeling studies. The number of invitations that would need to be sent to obtain 400 responses was estimated based on the actual response rate achieved by each survey mode in the case study. All unit costs of materials and labor, as well as proportions of respondents receiving the second mailing of the questionnaire, adopted in the cost-effectiveness analysis are actual costs and proportions associated with the case study.

1) Printing and mailing costs. This includes four contact mailings for both the mail-only and mixed modes, and two contacts for the internet-only mode. One hundred percent of people in the mixed and mail-only modes received at least three contacts and 92% received a second questionnaire. One hundred percent of people in the internet-only group received two contacts. The cost of including a cash incentive for the mail-only mode was included in the cost of the second mailing.

2) Labor costs. Three categories of labor costs were recognized: a) administrative and clerical costs associated with data collection (creating a sample plan, assembling and mailing contact materials

and data entry); b) development of the online survey for the internet-only and mixed survey modes; and c) Spanish language translation costs. Labor costs associated with data collection are variable and increase with the number of invitations sent out. Online survey development and Spanish translation costs, on the other hand, are fixed because there is zero marginal cost associated with an increase in the number of invitations. The cost of researcher time is assumed to be the same for all modes and has been excluded from the analysis.

3) Purchase of the sample addresses. Purchase of the address list is fixed at $500 for up to 1200 addresses, and then costs increase at a lower marginal rate of $0.09 for each additional address beyond 1200.

Sensitivity analyses (±20% and ±50%) from base case levels of variables of interest were conducted to test the robustness of the results to changes in 1) response rates, 2) target number of respondents, 3) level of printing and mailing costs, and 4) level of labor costs. A fifth sensitivity analysis was performed on the proportion of households that received both English and Spanish language contact materials.

3.4 Econometric Model

The multinomial logit model (MNL) is the most commonly used model for choice modeling datasets. Sample data from each of the three survey modes were fit to the MNL separately. The theoretical foundations of the MNL are random utility maximization (Mcfadden 1973) and the characteristics theory of value (Lancaster 1966). Random utility explains that the utility associated with a particular alternative from a choice set is composed of both an observable and a random component,

$$U_j = V(x_j, p_j;\ \beta) + \varepsilon_j \qquad (7.1)$$

where U_j is the true but unobservable utility associated with the consumption of profile *j*, *V* is the systematic indirect utility function, x_j is a vector of the attribute levels associated with profile *j*, p_j is the cost of profile *j*, β is a vector of preference parameters, and ε_j is a random error term. An individual will only select alternative *i* over alternative *j* if the utility associated with alternative *i* is greater than the utility from alternative *j.*

Assuming the errors in the regression can be described by a Gumbel distribution and are independently and identically distributed, the probability that an individual will select alternative *i* over alternative *j*, can be expressed as

$$P(i|C) = \frac{\exp(\mu V_i)}{\sum \exp(\mu V_{j)}} \tag{7.2}$$

where μ is a scale parameter inversely proportional to the variance of the error term. By assuming constant error variance, this parameter can be set to equal one (Ben-Akiva and Lerman 1985). Two MNL specifications were fit in this study. The first model contained only the choice attributes, represented by equation (7.3). Preferences are assumed to be homogeneous across respondents, which may not hold true because there are individual characteristics that are likely to explain some portion of the preferences that people have toward environmental goods. The second model specification, represented by equation (7.4), was expanded to include socioeconomic and attitudinal characteristics of respondents to account for preference heterogeneity,

$$P_n(i|C_n) = \frac{exp(\beta_{ni}X_{ni} + \alpha C_{ni} + \tau Q_{ni})}{\sum exp(\beta_{nj}X_{nj}\ \alpha C_{nj} + \tau Q_{nj})} \tag{7.3}$$

$$P_n(i|C_n) = \frac{exp(\beta_{ni}X_{ni} + \alpha C_{ni} + \tau Q_{ni} + \gamma R_n X_i)}{\sum exp(\beta_{nj}X_{nj} + \alpha C_{nj} + \tau Q_{nj} + \gamma R_{nj})} \tag{7.4}$$

where X_{ni} is a vector of terms for the attribute levels encountered by individual *n*; β_{ni} is a vector of associated estimated coefficients; C_n is the cost attribute associated with each alternative and α is the associated coefficient; Q_{ni} is an alternative specific constant (ASC), taking a value of 1 for status quo alternatives and zero otherwise, with an associated coefficient of τ; R_n is a vector of case-specific socioeconomic characteristics, included to account for heterogeneity in preferences across respondents, and have an associated coefficient of γ; and i and j are as previously defined.

In order to obtain policy relevant interpretations of the estimated coefficients, the marginal effects of each attribute must be calculated. Based on the models represented by equations (3) and (4), for attributes 1 through K the average household marginal willingness to pay (MWTP) for a one-unit improvement in the *kth* attribute can be estimated by equation (7.5)

$$\text{MWTP} = \left(\frac{\beta_n+\sum_{m=1}^{M}\ \gamma_{nm}G_m}{\alpha+\sum_{m=1}^{M}\ \theta_{nm}G_m}\right) \tag{7.5}$$

where G represents the fraction of the study area population that falls into each of the m socioeconomic or attitudinal categories (as reported in Table 2) and all other parameters are defined as above. Based on the method used by Han et al. (2008), equation (7.5) produces adjusted average household MWTP that corrects for the potential that survey respondents were not representative of the demographic characteristics of the study area as a whole.

4. Results

4.1 Response Rates and Sociodemographic Characteristics

The survey yielded 1,226 total complete returned surveys. As shown in table 2, the mail-only survey mode had the highest effective response rate, at 42%. The response rate for the mixed-mode was 39%. At 4.5%, the internet-mode had the lowest response rate. Of the 345 total responses to the mixed-mode invitations, 291 were completed with mail hard-copy and 54 were completed on the internet. Overall, the survey respondents were on average older, better educated, wealthier, and more likely to be male than residents of the study area as a whole (Table 3).

Table 2. Response Rates by Mode

	Internet	Mail	Mixed
Invitations sent	16,775	511	1,019
Undeliverable invitations	1,451	57	125

Delivered invitations	15,324	454	894
Complete responses	692	189	345
Overall response rate	**4.5%**	**42%**	**39%**
MT response rate	5.9%	54%	50%
CO response rate	4.5%	35%	36%
AZ response rate	3.1%	35%	29%
Urban response rate [a]	3.9%	34%	34%
Rural response rate [a]	4.3%	39%	29%

Notes:

a: Response rates for urban and rural residents cannot be compared to overall response rates or state rates because urban and rural response rates are calculated using the total number of sent invitations, rather than the number of delivered invitations the number of undeliverable invitations is not known across urban and rural residents.

Response rates were highest in Montana and lowest in Arizona, across all survey modes. In the collected sample, 66% of respondents lived in metro counties. People who live in rural areas responded at a higher rate than urban residents to both the internet-only and mail-only survey modes. However, at 4.3% and 3.9%, respectively, the difference in internet only response rates between rural and urban residents was not large. Urban residents responded at a higher rate to the mixed survey mode.

Using Chi-Squared and ANOVA tests, significant differences were found between the sociodemographic characteristics of respondents to alternative survey modes. Respondents to the internet-only survey mode were statistically significantly less likely to be senior citizens, have less than a college degree, and reside in a household earning less than $100,000 per year than respondents to other survey modes. Respondents to the mail-only survey mode were significantly more likely to be male than respondents to the internet-only and mixed survey modes. Internet access amongst respondents in the internet survey mode was higher than amongst respondents to either the mail or mixed survey modes.

All survey modes produced samples that were more likely to be senior citizens, male, high income and college educated, than the population of the study area as a whole. The sample from the internet survey contained a significantly larger amount of high income and college educated individuals. The internet sample was composed of significantly fewer senior citizens than the other modes. The sample from the mail survey was the most likely to over-represent males and climate change skeptics. Overall, the internet survey mode appears to exacerbate the differences between the collected sample and population of the study area in terms of income level and education, relative to the other survey modes. However, it produced a more represented sample in terms of gender and proportion of senior citizens. The mixed mode did not provide a significantly more representative sample of the population compared to the internet, despite offering the ability to sample people without access to the internet.

Table. 3. Mean Value of Sociodemographic Characteristics by Mode and Study Area Population

Characteristic	Internet	Mail	Mixed	Population [a]
MALE	62%	65%*	62%	50%
SENIOR [b]	32%*	39%	40%	14%
HIGHINC	25%*	24%	24%	20%
COLLEGE	61%*	47%	47%	31%
INTERNET ACCESS [d]	98%*	91%	90%	74% [c]
SKEPTIC	47%	55%*	47%	49%

Notes:

* Indicates statistically significant difference from sample mean of the other survey modes. Based on Chi-Squared or ANOVA tests.

a Based on the weighted average of the populations of Arizona, Colorado, and Montana. Source: Census Bureau (2010a)

b Senior citizens are defined as age 65 and older.

c State-specific census data was only available for high speed internet access, while the survey did not specify high-speed or not. Nationally, the rate of high-speed internet access is only one percentage point lower than the rate of access to any type of internet access, so these numbers should be comparable. Source: File and Ryan (2014)

d : Proportion of household that own a computer and have internet access.

4.2 Willingness to Pay

Table 4 presents parameter estimates from three MNL models, estimated for each survey mode separately. Sociodemographic and attitudinal characteristics that vary across the survey modes account for some of the heterogeneity in choice that is not explained by the attribute levels.

Because of the interaction terms in the model, the coefficients on the attributes represent base-case preferences. The base case in these models are people who are younger than 65 years old, do not have a college education, make less than $100k per year and believe in man-made climate change. The attribute coefficients have the expected signs for all of the survey modes, but the statistical significance varies from mode to mode. For the internet mode, all attributes except WILDFIRES are statistically significant. For the mail mode, HOMES, AIRDAYS, and WILDFIRES are all statistically insignificant for the base case. For the mixed mode, HOMES and WILDFIRES are statistically insignificant.

Table 4. Regression Results, MNL Interactions model

	Internet		Mail		Mixed	
	Estimate	SE	Estimate	SE	Estimate	SE
HOMES	0.00987**	0.00459	0.0106	0.00673	0.00618	0.00592
AIRDAYS	-0.0505***	0.00966	-0.0275	0.0174	-0.0307**	0.0120
WILDFIRES	-0.0254	0.0220	-0.0258	0.0472	-0.0340	0.0284
FORESTS	0.0379***	0.00363	0.0277***	0.00697	0.0285***	0.00453
BILL	-0.00366***	0.000890	-0.00355**	0.00156	-0.00388***	0.00121
ASC	0.298***	0.0587	0.468***	0.104	0.287***	0.0902
SKEPTIC X HOMES	-0.00933**	0.00412	0.00566	0.00782	-0.00282	0.00659
SKEPTIC X AIRDAYS	0.0379***	0.00908	0.00478	0.0176	-0.0185	0.0144
SKEPTIC X WILDFIRES	0.0288	0.0222	0.0603	0.0460	-0.0172	0.0341
SKEPTIC X FORESTS	-0.0149***	0.00341	0.00923	0.00710	-0.0145***	0.00523
SKEPTIC X BILL	-0.00218**	0.000939	-0.00248	0.00189	-0.00160	0.00146
HIGHINC X HOMES	0.00847*	0.00463	-0.0164	0.0117	0.00508	0.00776
HIGHINC X AIRDAYS	-0.00581	0.0107	-0.0121	0.0322	-0.0122	0.0208
HIGHINC X WILDFIRES	-0.0274	0.0262	-0.106*	0.0551	0.00939	0.0398
HIGHINC X FORESTS	-0.000636	0.00391	0.00268	0.0102	0.0183**	0.00812
HIGHINC X BILL	0.000401	0.00104	0.000185	0.00279	-0.000720	0.00185
COLLEGE X HOMES	0.00137	0.00467	0.0100	0.00906	0.00535	0.00655
COLLEGE X AIRDAYS	-0.0266***	0.00936	-0.0401*	0.0209	-0.0264*	0.0150
COLLEGE X WILDFIRES	-0.00583	0.0232	0.00518	0.0538	0.0120	0.0357
COLLEGE X FORESTS	0.00291	0.00359	0.0153*	0.00845	0.0133**	0.00519
COLLEGE X BILL	-0.00104	0.000954	-0.00248	0.00224	-0.000902	0.00148
SENIOR X HOMES	-0.000234	0.00447	-0.0107	0.00834	-0.00771	0.00688
SENIOR X AIRDAYS	0.00645	0.00953	-0.0106	0.0156	0.0183	0.0140
SENIOR X WILDFIRES	-0.0430*	0.0240	0.00587	0.0475	-0.0200	0.0348
SENIOR X FORESTS	-0.00334	0.00362	-0.00688	0.00712	0.000420	0.00533
SENIOR X BILL	-0.000945	0.000999	0.00266	0.00187	-0.00135	0.00151
N	7620		1956		3492	
Log-likelihood	-2367.1		-557.6		-1042.3	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Comparison of the statistical significance of the interaction terms across the three survey modes suggests that some of the sociodemographic and attitudinal characteristics affect choice differently for the different modes. Despite the differences in preferences between the survey modes, indicated by the differences in the models, there are no significant differences in MWTP between the survey modes. Table 5 reports the average monthly household MWTP for each survey mode, estimated using equation (5). A 95% confidence interval for each choice attribute was estimated with 500 bootstrap repetitions using the method described by Efron and Tibshirani (1986). While the mean values of MWTP vary somewhat between the survey modes, in all cases the 95% confidence intervals overlap, indicating no statistically significant differences. Although no formal tests of precision were performed, the confidence intervals are generally tighter for the estimates from the internet sample that for the other survey models, likely as a result of the larger sample collected with the internet survey.

Table 5. WTP by Survey mode, MNL Interactions model

	Internet			Mail			Mixed		
Attribute	Average household MWTP ($)	95% confidence interval ($)		Average household MWTP ($)	95% confidence interval ($)		Average household MWTP ($)	95% confidence interval ($)	
HOMES	1.47	0.38	2.56	2.29	0.31	4.27	1.22	-0.28	2.72
AIRDAYS	-8.03	-10.53	-5.52	-8.15	-14.27	-2.02	-9.05	-12.98	-5.12
WILDFIRES	-4.88	-9.89	0.13	-3.08	-14.75	8.59	-7.49	-14.21	-0.77
FORESTS	6.11	4.62	7.60	7.14	3.35	10.93	5.59	3.71	7.48
ASC	81.39	19.55	143.23	131.88	-960.5	1224.2	73.96	-23.05	170.96

4.3 Cost Effectiveness

Based on detailed survey cost records from the case study, Table 7.6 reports the cost to achieve 400 completed survey responses for each survey mode. Results from the cost comparison reveal internet-only to be the most cost effective of the survey modes, with a cost per response of $61 (Table 7.6). Mail-only was the second most cost-effective survey mode, with costs per response of $70. The mixed survey mode was the least cost-effective option.

Table 7.6. Survey implementation costs by mode, target sample of 400

	Internet	Mail	Mixed
Response Rate	4.5%	42%	39%
Number of Invitations	8,889	962	1,026
Mailing Costs			
1st Contact Mailing	$5,764	$624	$665
2nd Contact Mailing [a]	n/a	$11,051	$9,736
3rd Contact Mailing	$3,771	$408	$435
4th Contact Mailing [b]	n/a	$8,397	$8,957
Total Mailing Costs	**$9,535**	**$20,479**	**$19,793**
Labor Costs			
Sample Design	$716	$716	$716
Admin & Clerical	$2,528	$5,141	$4,716
Website Design Labor	$9,410	n/a	$9,410
Spanish Translation	$1,000	$1,000	$1,000
Total Labor Costs	**$13,648**	**$6,857**	**$15,837**
Sample Address Costs			
First 1200	$500	$500	$500
After the first 1200	**$688**	**0**	**0**
Total Other Costs	**$1,188**	**$500**	**$500**
Total Costs [c]	**$24,371**	**$27,836**	**$36,130**
Cost per Response [d]	**$61**	**$70**	**$90**

Notes:

a Costs included in the second mailing include: postage for the mail packet, copies of the 16-page color surveys, return envelope and postage, and $2 incentive for mail only. This also includes a fraction of packets with a Spanish language version of the survey too. Double the number of questionnaires must be printed and higher postage must be paid for each household that receives both languages in the mail-only and mixed modes. Accommodating two languages with the internet-only mode requires only that contact materials be printed double-sided with a different language on each side.

b Costs included in the second mailing include: postage for the second mail packet, sent to addresses had not returned the first packet, copies of the surveys, return envelope and postage. Spanish language versions of the survey too are included for a fraction here as well.

c Total costs is the sum of total mailing costs, total labor costs, and total other costs.

d Cost per response is total costs divided by the target response number of 400.

Results from the sensitivity analyses are displayed in Figures 1 to 5. The base case parameter values for each survey mode in Figures 7.1, 7.3 and 7.4 can be found in Table 7.6. The base case parameter value in Figures 7.2 and 7.5 are the same for all survey modes, namely 400 responses and 14% of invitations with a Spanish language option, respectively.

The sensitivity analyses revealed that the finding that the mixed mode is the least cost effective is robust against changes in the levels of variables on which the sensitivity analyses were conducted. This is unsurprising given the combination of high fixed website design labor costs and high mailing costs. In addition, the response rate was lower than the mail-only mode. A likely explanation for the lower response rate relative to the mail only mode is the absence of the incentive payment. The lower response rate for mixed-mode than the mail-only may be a result of the $2 incentive that was provided in the mail-only contact material, and not in the mixed-mode material. Incentives have been shown to produce higher response rates (Mooney et al. 1993).

With respect to both response rate and target response number, there is a point at which mail contact becomes more cost effective than internet-only. For response rates 50% higher than the base case for each survey mode[18], the cost per response achieved by the mail only mode becomes smaller than for internet-only; $50 versus $52, respectively (Figure 7.1). Given a target number of responses of 400, Figure 1 does indicate that the cost per response for the mail only mode would be equivalent to the base case costs for internet only with a 20% improvement in response rate (to 50.4%). At a target of 200 responses, 50% below the base case, the cost per response for mail only is lower than for the internet only mode (Figure 7.2). However, Figure 7.2 also reveals that as the target response number increases, the cost advantage of internet over mail only becomes larger.

[18] This is equivalent to a mail only survey response rate of 63% and an internet only response rate of 6.8%.

Figures 7.3 and 7.4 highlight the relative sensitivity of the internet only and mail only survey modes to mailing and labor costs, respectively. When mailing costs are low or labor costs high, the mail mode becomes more cost-effective than the internet mode.

Sensitivity analysis with respect to the proportion of households that receive both English language and Spanish language materials revealed that the cost advantage of the internet mode over the mail mode becomes larger as the proportion of households that receive both language versions of the survey increases (Figure 7.5). The inclusion of a Spanish language option increases the costs of printing and mailing much more for mail than internet surveys.

Figure 7.1. Sensitivity of cost per response to response rate

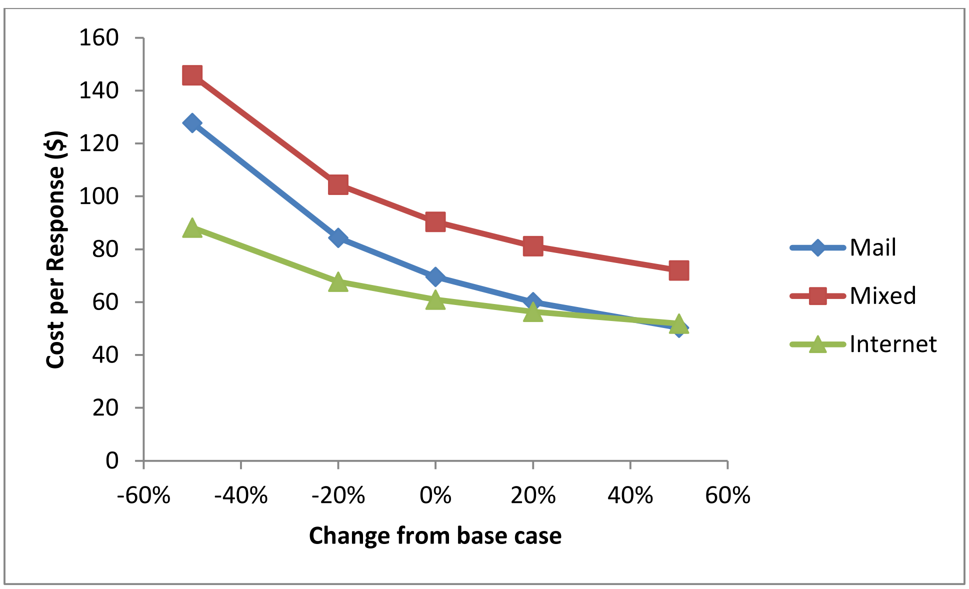


Figure 7.2. Sensitivity of cost per response to target response number (base case is 400 for all survey modes)

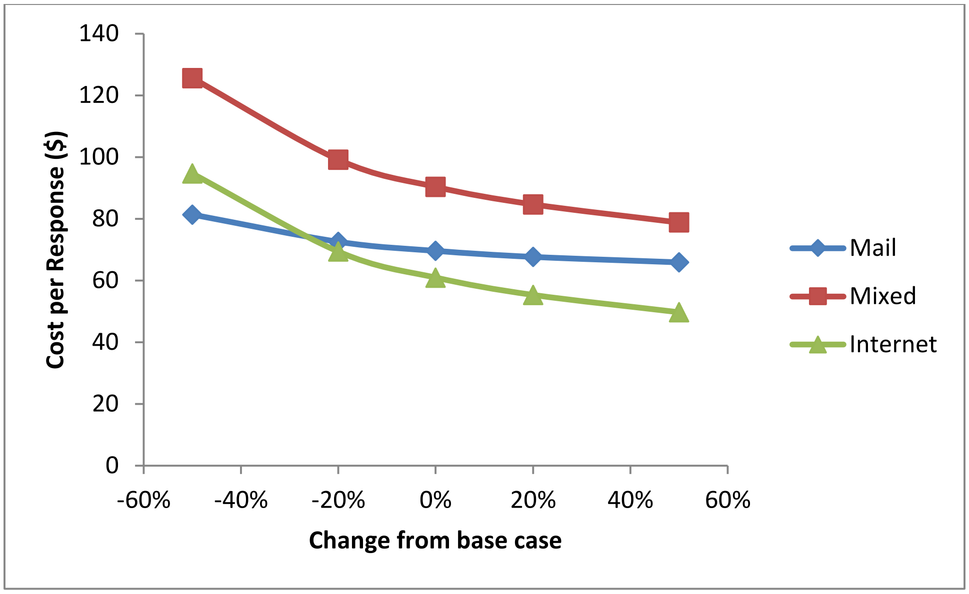


Figure 7.3. Sensitivity of cost per response to mailing costs

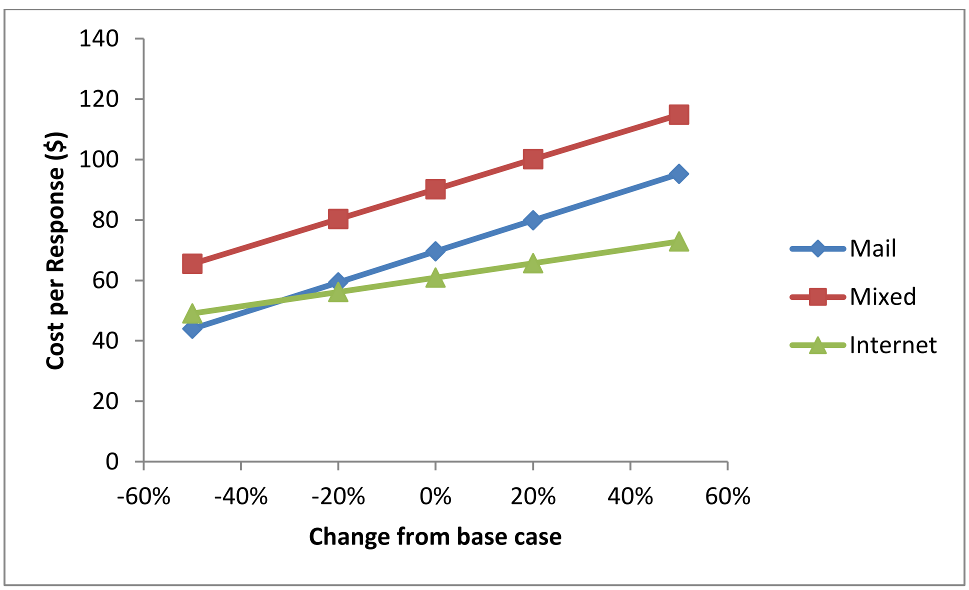


Figure 7.4. Sensitivity of cost per response to labor costs

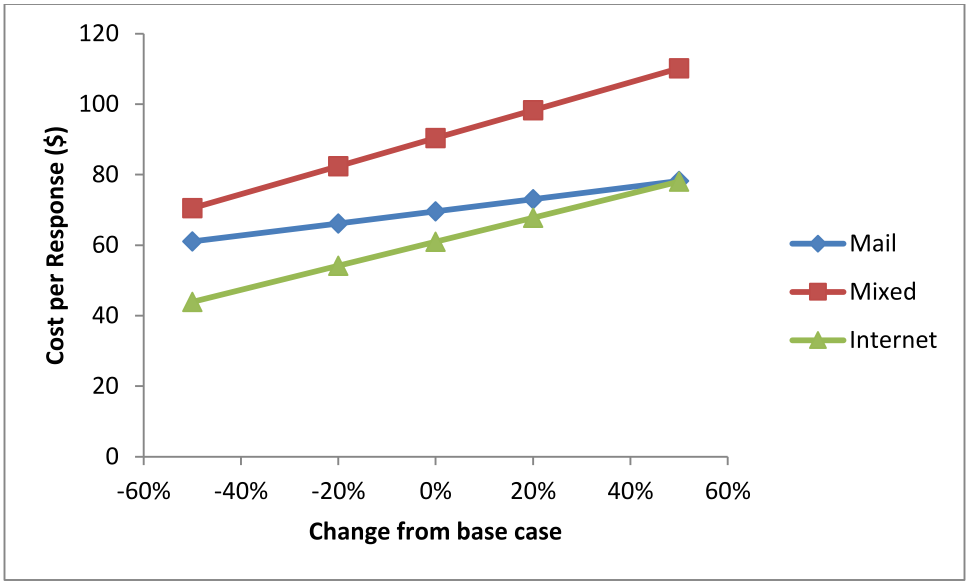
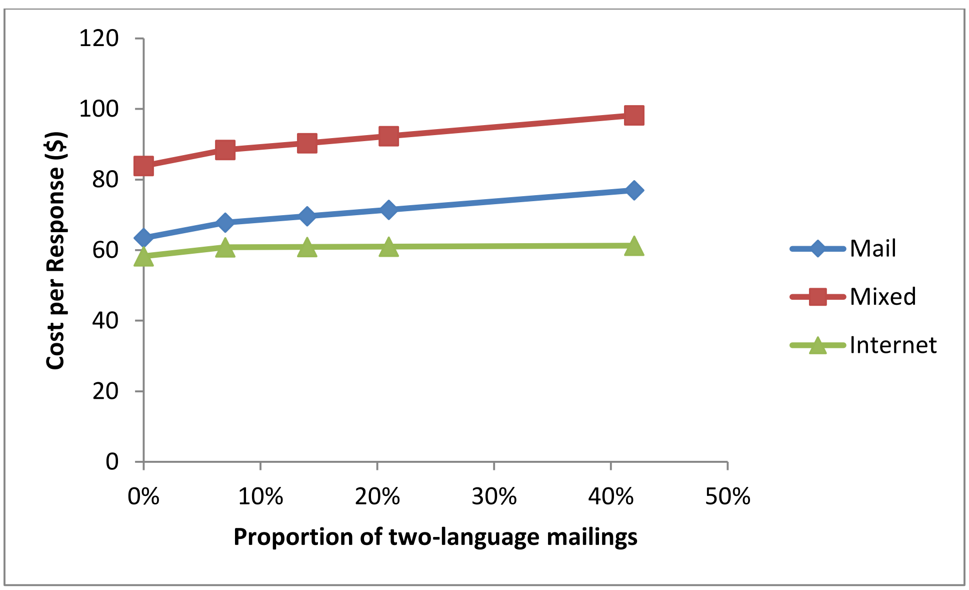


Figure 7.5. Sensitivity of cost per response to proportion of two-Language mailings (base case is 14% for all survey modes)



5. Discussion and Conclusion

This paper makes important contributions to the literature evaluating the cost-effectiveness of alternative survey modes for non-market valuation. The comparison is made between internet only, mail only and mixed (internet and mail) survey modes for an application of the choice modeling non-market valuation method to estimate public preferences toward woody biomass energy in Arizona, Colorado and Montana. The evaluation has been made on the basis of: (a) how representative the sociodemographic characteristics of the sample are relative to the population and whether there are differences in MWTP between the survey modes (sample bias); and (b) the cost-effectiveness (survey cost per usable response).

Comparison of the sociodemographic profiles of the samples collected by the different survey modes reveals that internet mode collected a sample that was significantly wealthier and more highly educated than the mail or mixed mode samples, and was farther from the mean value of the study area population for these characteristics. However, the internet sample was more representative than the other modes in terms of age by having a significantly lower proportion of seniors. These findings are consistent with other studies that have found internet samples to be younger, more highly educated, and wealthier than mail samples (Olsen 2009, Macdonald et al. 2010). Based on these results, it is not clear that one survey mode produced a sample that is clearly better than the samples collected by the other survey modes.

Consistent with the finding that sociodemographic characteristics of respondents to the three survey modes are similar, there was no evidence of statistically significant differences in MWTP for choice attributes between the survey modes. Since the purpose of choice modeling is to estimate the value of non-market goods, the lack of significant differences in MWTP between the survey modes reduces concerns about sample bias due to survey mode.

This suggests the standard approach to account for potential differences in preferences between the sample and the population through the inclusion of sociodemographic control variables in the MNL and weighting by population characteristics in the calculation of MWTP are sufficient to account for sample bias. However, findings by previous studies are mixed. Olsen (2009), who accounted for preference heterogeneity with a random parameters model specification, found no significant differences in WTP between internet and mail survey modes. Bell et al. (2011) however, did find significant differences in economic measures between internet and mail survey modes, even when accounting for sociodemographic characteristics in a two-tailed Tobit regression analysis. The case study provided no argument to favor one survey mode over another on the basis of sample bias.

The internet survey mode was found to be the most cost-effective of the three modes examined. This facilitates a larger sample to be collected for a given budget constraint, which may result in the most precise estimates of MWTP. The mixed survey mode was the least cost-effective and, given the statistically insignificant differences in sample bias between survey modes, the mixed survey mode must be considered inferior to the two alternatives examined in this study. As a result of the low marginal cost of extending additional invitations once the fixed costs of setting up the internet survey have been incurred, the cost savings increase as the target number of responses increases. The cost advantages of the internet survey mode are even larger if a multi-lingual approach is required. Sensitivity analyses highlighted that mail only surveys are more cost-effective than internet surveys when the target number of respondents is small and when the response rate is high. This is due to the relatively high fixed costs associated with setting up internet survey web pages and low marginal cost of additional invitations for the internet survey mode, versus the relatively low fixed costs and relatively high marginal costs of additional invitations for the mail mode. Figure 7.1 suggests the response rate would have to be about 63% (+50% from the base case) for the mail only survey mode to be more cost-effective than internet only.

The sensitivity analysis in Figure 7.3 revealed that a smaller survey than developed for the case study (with lower printing and postage costs) could make the mail only survey mode more cost-effective than internet only. Average salaries in the state of Montana, from which the case study survey was developed and administered, are among the lowest of all states in the United States. In states where labor costs are high, the difference in cost effectiveness between internet and mail may be smaller, as highlighted in Figure 7.4. However, given the low marginal costs of the internet survey mode, internet only must become the most cost-effective survey mode as target number of responses increases and the response rate decreases.

Based on the criteria examined in this study, the internet survey mode is found to be the preferred survey mode for collecting stated preference nonmarket valuation data. The internet mode is the most cost effective of the three survey modes, offering the ability to collect a larger sample for a given budget. Although some significant differences in the characteristics of the collected sample were found between the survey modes, estimates of WTP did not differ significantly.

7.6 Chapter 7 References

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Chapter 8

General Discussion and Conclusions

In order to address the pressing threat that climate change presents to humanity, and achieve the commitments that have been made to reducing fossil fuel consumption, the United States must increase the amount of renewable energy it produces. In order to make socioeconomically efficient decisions about how to supply the country's energy needs, the externalities associated with alternative sources of energy generation need to be quantified. This research contributes to the goal of supporting socioeconomically efficient decision-making about energy generation by quantifying the nonmarket costs and benefits associated with one energy source – woody biomass energy. The choice modelling method was used to analyze social preferences toward energy produced with woody biomass harvested from the public forests in Arizona, Colorado and Montana. Public willingness to pay was estimated for energy generated with woody biomass and the potential associated effects on forest health, likelihood of large wildfires, and local air quality.

Findings from the choice modelling study were used to produce three manuscripts, each of which makes a unique contribution to the goal of supporting socioeconomically efficient decision making in forest management and renewable energy policy in the Mountain West. In this chapter, the key results from the three manuscripts and their collective implications for the potential of woody biomass energy generation in the Mountain West are discussed. Then, limitations of this study are considered. Finally, potential extensions of this research are explored.

8.1 Key Research Findings

Results from Manuscript 1 revealed that Montana residents have positive MWTP for increased utilization of woody biomass from public forests, to produce energy, avoid degraded air quality, and improved forest health in the state. Montanan's reserved their highest WTP for improved forest health. MWTP to avoid additional large wildfires, however, was not significantly different than zero. A potential explanation for the insignificance of the wildfires attribute lies in the relationship between wildfires and air quality. The main form of interaction with wildfires for many people is through the impact that wildfire smoke has on air quality. If preferences toward large wildfires is indeed driven mostly by air quality concerns, rather than concerns for the protection of homes and watersheds, then some of the strength of preference toward wildfires may have been captured by AIRDAYS.

MWTP for woody biomass energy, air quality, and forest health diminishes as their respective levels increase. The implications of diminishing MWTP for woody biomass energy generation are important. As shown in Figure 5.2, TWTP for homes powered with wood in Montana begins to decrease around 45,000 homes, revealing that the socioeconomically efficient number homes powered with woody biomass from public forests in Montana is no more than approximately double the current amount of 20,000 homes.

In Manuscript 2, preferences for woody biomass energy in the full study area of Montana, Colorado, and Arizona were analyzed, with a focus on heterogeneity in preferences. Results revealed that the average household in the study area has statistically significant positive MWTP for an increase in energy generated with woody biomass from restoration treatments on public forests. Mean annual household MWTP for the HOMES attribute is $17.10, and when aggregated for the 4.75 million household in the study area, WTP for a 10% increase in the number of homes powered with woody biomass is substantial, at $163 million annually (Chapter 6, Table 6.8). However, when viewed through this lens of WTP for a 10% improvement, woody biomass energy generation is the smallest of any attribute in the survey.

Just as was found for Montana residents, respondents for the full study area reserved their highest MWTP for forest health (Table 6.8). This is consistent with the large majority of respondents that believe that forests are in need of restoration. MWTP was second highest for the WILDFIRES attribute. Respondents that live in a forested ecoregion have higher MWTP to avoid large wildfires. This is consistent with the hypothesis that WTP to avoid large wildfires is driven by direct benefits of reducing the risk to one's own private property. MWTP for AIRDAYS was smaller than for forest health and wildfires, but larger than for HOMES. It appears that people who live in communities with better air quality are less willing to accept reduced air quality than people who live in communities with poorer air quality to begin with. The lower willingness to accept degraded air quality amongst residents of communities without a history of poor air quality may be partially explained by the concept of loss aversion. Loss aversion is one explanation for the endowment effect, in which individuals value an item more highly if they already own it. Loss aversion states that once an individual owns or possesses something, giving it up feels like a loss. Therefore individuals who already possess good air quality may value marginal changes in their air quality more highly than individuals exposed to lower air quality.

Preferences toward woody biomass energy and its potential associated effects are not homogenous across the population. Sociodemographic characteristics and attitudes are significant determinants of preferences. The presence of four groups (woody biomass believers, biomass skeptics, respondents with low WTP, and attribute non-attenders) with distinct preferences within the population, as indicated by the results of the LCL model, suggests that distributional effects may exist in the impacts of changes in public land management and energy policies. Results from the LCL model reveal a class of respondents that are disengaged on the issue of public forestland management for energy as a result of climate change beliefs and geography. The attributes resonated less strongly with these respondents, who are less likely to believe in anthropogenic climate change and less likely to live in forested areas. As revealed by the results of the LCL model, support for woody biomass energy is not universal. A class of respondents was identified who are concerned about climate change and the conditions of public forests, but for whom woody biomass energy is not viewed as a valid method of addressing these issues, as indicated by a MWTP for HOMES that is not statistically different from zero. These results reveal some controversy surrounding woody biomass energy and suggest that some conflict can be expected if public forests are managed to produce more woody biomass energy. A collaborative approach to public lands management that allows for input from multiple stakeholder groups offers one potential solution for dealing with conflicting viewpoints with regards to the utilization of woody biomass for energy generation.

In addition, MWTP for HOMES diminishes rapidly (as shown in Figure 5.2 & Figure D.1 in Appendix D), suggesting that the public's desire for more woody biomass energy from public forests is satiated rather quickly. It appears that some respondents view woody biomass as an inferior source of renewable energy and would prefer that their renewable energy come from another source. It may also be the case that biomass harvest is viewed as being in conflict with other goods and services provided by public forests. However, these results may, in part, be a reflection of the maximum sustainable level woody biomass energy produced with residues from restoration treatments on public forests, which was defined in the survey as 50,000 home equivalents of energy, in each state annually.

State of residence was not a significant determinant of preferences and WTP did not vary significantly between states. Although MWTP for HOMES and WILDFIRES was not significantly different than zero in Arizona, 95% confidence intervals overlap between the three states for all attributes (Appendix D, Table D.2). Despite the lack of a statistical difference between the states, these results can't necessarily be extended to states that were not sampled in this study and cannot be assumed to hold true for the USA as a whole. However, the fact that no significant differences in preferences were found between the residents of Arizona, Colorado, and Montana is an encouraging finding regarding the potential application of benefits transfer with these results.

The third manuscript compared three different survey modes for collecting nonmarket valuation data. Based on the results of the third manuscript, for future data collection efforts, an internet survey mode is recommended because of its superior cost efficiency relative to mail-only and mixed survey modes. Although there were differences in the samples collected by the alternative survey modes, it did not result in statistically significant differences in estimates of MWTP. The cost effectiveness of an internet survey will be best utilized if the target number of responses is large.

The main findings from this research suggest that the public is willing to pay a premium for some increase in energy produced with woody biomass harvested from public forests. The estimated MWTP values can be used by policy makers and public land managers to determine to what degree the social benefits of utilizing the residues from forest restoration or fuel treatment programs to generate energy offset the costs associated with the programs.

From a socioeconomic perspective, the production of more energy from woody biomass than the free market will provide is likely more efficient because of the failure of the free market to account for nonmarket benefits. However, MWTP for woody biomass energy decreases rapidly, indicating that the public does not wish to see large amounts of energy produced this way. WTP for HOMES is smaller than for the other attributes, suggesting people would not be willing accept significant decreases in forest health, increases in the likelihood of large wildfire, or reduced air quality in their community in order to achieve higher amounts woody biomass energy. On the other hand, the WTP for the non-energy attributes suggests that if increased woody biomass energy generation can facilitate more forest treatments that improve the condition of public forests, substantial additional benefits may be gained.

The potential benefits associated with woody biomass energy, for which residents of the Mountain West are willing to pay, are more likely to be generated in certain situations than others. Forest health can be improved and the risk of large wildfires reduced through mechanized treatments of forests that are departed from historic conditions. Air quality can be improved through the utilization of residues that would otherwise have been burned in open piles in the forest. These benefits are less likely to be generated in other situations, such as chipping whole trees to produce energy feedstock, or converting forestland to grow trees specifically for energy. As a result, there are some cases where woody biomass energy generation is likely to be socioeconomically efficient, and some cases in which it is not likely to be.8.2 Limitations of this Research and Opportunities for Future Research

Although the results of this research can provide useful information to facilitate efficient decision making about the harvest and utilization of woody biomass from public forests in the Mountain West, they are not without limitations. Some limitations arise as a result of the large geographic size of the study area. The study area is ecologically diverse and encompasses a wide range of forest and other ecosystem types. However, because of the need to create a survey instrument that was applicable across the entirety of the study area, the attributes and potential impacts had to be defined in broad terms that may not capture the diversity of the ecological characteristics of the study area. The large study area, as well as the need to not overwhelm respondents with information also required the complexity of the relationships between forest treatments, forest health and wildfire dynamics to be simplified in the survey materials. Results may therefore be unable to capture the richness of preferences of people who have well defined preferences that vary for specific landscapes or forest types.

The results provide only a limited understanding of how preferences toward woody biomass energy fit in relation to preferences toward other sources of renewable energy. Respondents were asked to rank their three most desired energy options to get them in the mindset that there are many renewable energy types. The low ranking of woody biomass energy relative to most other options presented in this question suggests that, while respondents expressed positive WTP for woody biomass energy, they may have preferred to have a different renewable energy option. Because the choice sets did not have the option to express their WTP for more than one type of renewable energy, and despite a survey designed to focus respondents on woody biomass energy, there may be some ambiguity as to whether the WTP expressed for woody biomass represents WTP specific to this particular source of energy, or if the preference may represent a general desire for more renewable energy, regardless of the source. A more formal exploration of preferences toward woody biomass relative to other renewable energy options offers a logical extension of this research to better support renewable energy policy-making. Further research is also needed to determine whether the preferences of residents of Arizona, Colorado, and Montana are applicable to other areas of the United States, and whether preferences toward energy generated with woody biomass harvested from private land differ significantly from biomass sourced from public forests. Another compelling extension of this research would be to conduct a case-study comparison of the socioeconomic efficiency of woody biomass energy from forest residues versus fossil fuel energy generation. This could be done by combining the results from this study with financial costs of woody biomass and fossil fuel energy generation, social costs of greenhouse gas and air pollutant emissions, and environmental damages from fossil fuel extraction.

APPENDIX A

Focus Group Participants and Brainstorming Materials

Table A.1. Participants in Missoula Focus Group

Name	Position	Affiliation
Julie Kies	Biomass Utilization Specialist	Montana Department of Natural Resources and Conservation
Brian Spangler	Renewable Energy Specialist	Montana Department of Environmental Quality
Scott Spaulding	Fisheries Program Leader	United States Department of Agriculture, Forest Service
Tom Power	Professor Emeritus - Economics	University of Montana
Amy Cilimburg	Director of Conservation and Climate Policy	Montana Audubon Society
Charlie Sells	Forester	Forestry Contractor
Chuck Roady	Vice President	Stoltze Lumber
Zach Porter	Western Montana Field Director	Montana Wilderness Association
Angela Farr	Regional Biomass Coordinator	United States Department of Agriculture, Forest Service
Dave Ryan	Member of the Board	Mountain Bike Missoula
Martin Twer	Bioenergy Specialist	Montana State University Extension Forestry
Rich Lane	Fiber Resources Manager	Boise Inc.

Table A.2. Participants in Denver Focus Group

Name	Position	Affiliation
Mike Eckhoff	Biomass Utilization Specialist	United States Department of Agriculture, Forest Service and Colorado State University
Christine Hoefler	Air Pollution Control Specialist	Colorado Department of Health and Environment
Phil Kastelic	Founder	Colorado Forest and Energy, LLC
Kurt Mackes	Professor of Forestry	Colorado State University
Sloan Shoemaker	Executive Director	Wilderness Workshop
Bruce Ward	President	Choose Outdoors
Chris Gaul	Energy Engineer	National Renewable Energy Laboratory

Table A.3. Participants in Flagstaff Focus Group

Name	Position	Affiliation
Patrick Rappold	Wood Utilization and Marketing Specialist	Arizona State Forestry
Mark Brehl	Wildland Fire Leadworker	Flagstaff Fire - Flag Watershed Protection
Heath Hildebrand	Plant Manager	Novo Power
Anne Mottek Lucas	Analyst	Mottek Consulting
Steve Gatewood	Director	Wildwood Consulting and Greater Flagstaff Forest Partnership
Diane Vosick	Director of Policy and Partnerships – Ecological Restoration Institute	Northern Arizona University
Nick Koressel	Energy Services and Sustainability	Northern Arizona University
Ethan Aumack	Conservation Director	Grand Canyon Trust

Figure A.1. Missoula Focus Group Brainstorming Map

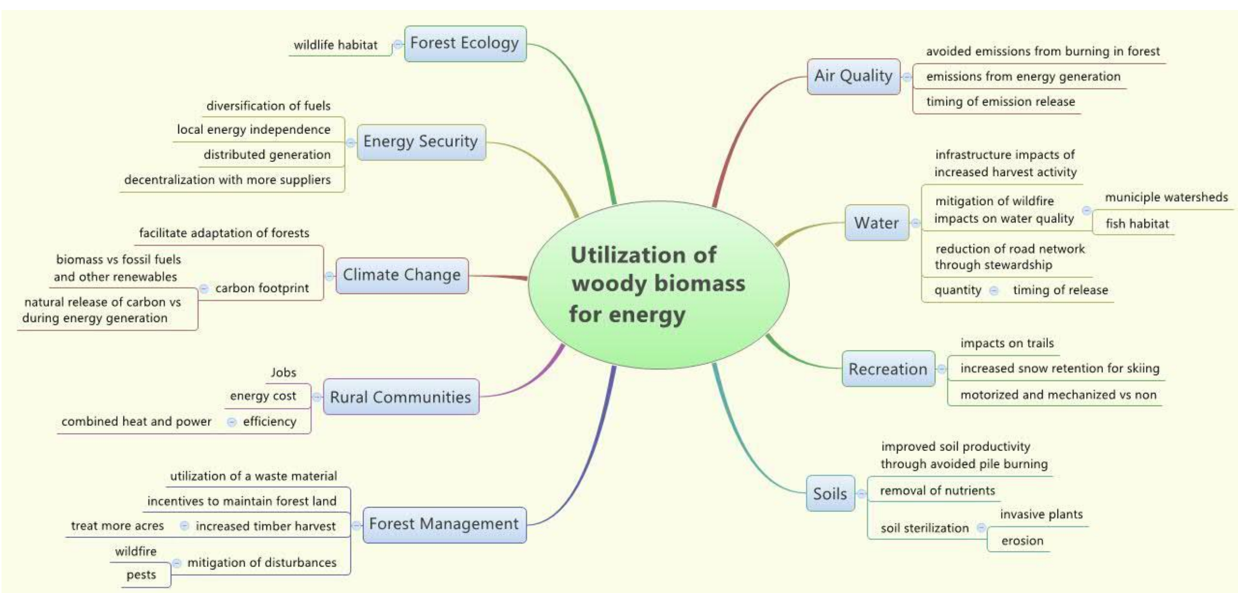


Figure A.2. Denver Focus Group Brainstorming Map

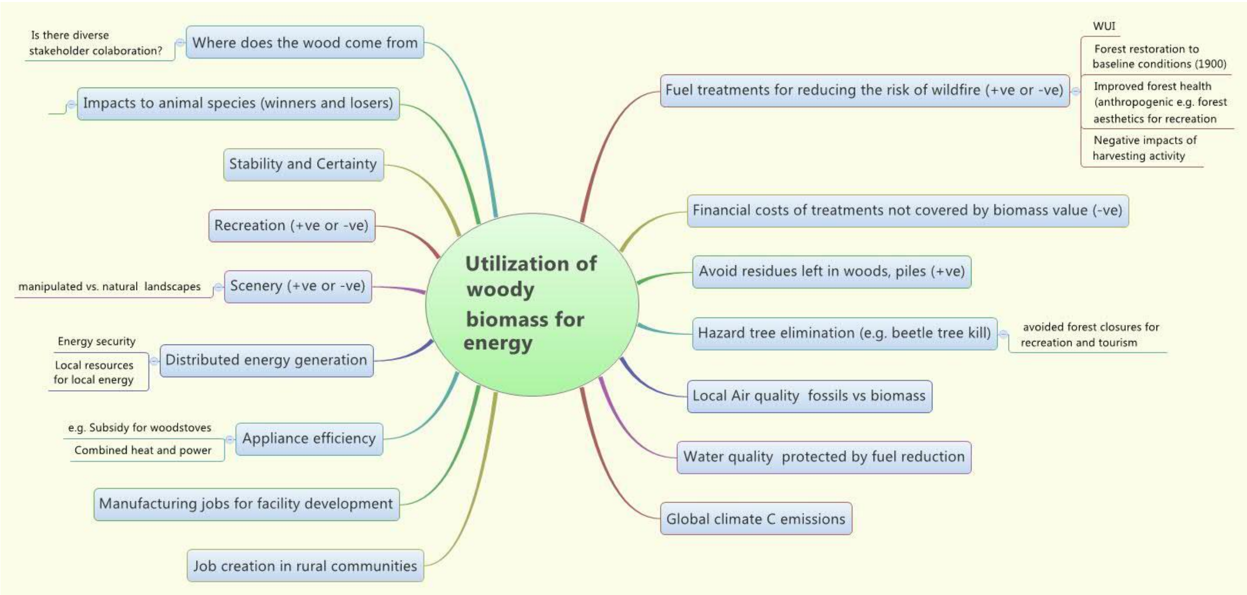


Figure A.3. Flagstaff Focus Group Brainstorming Map

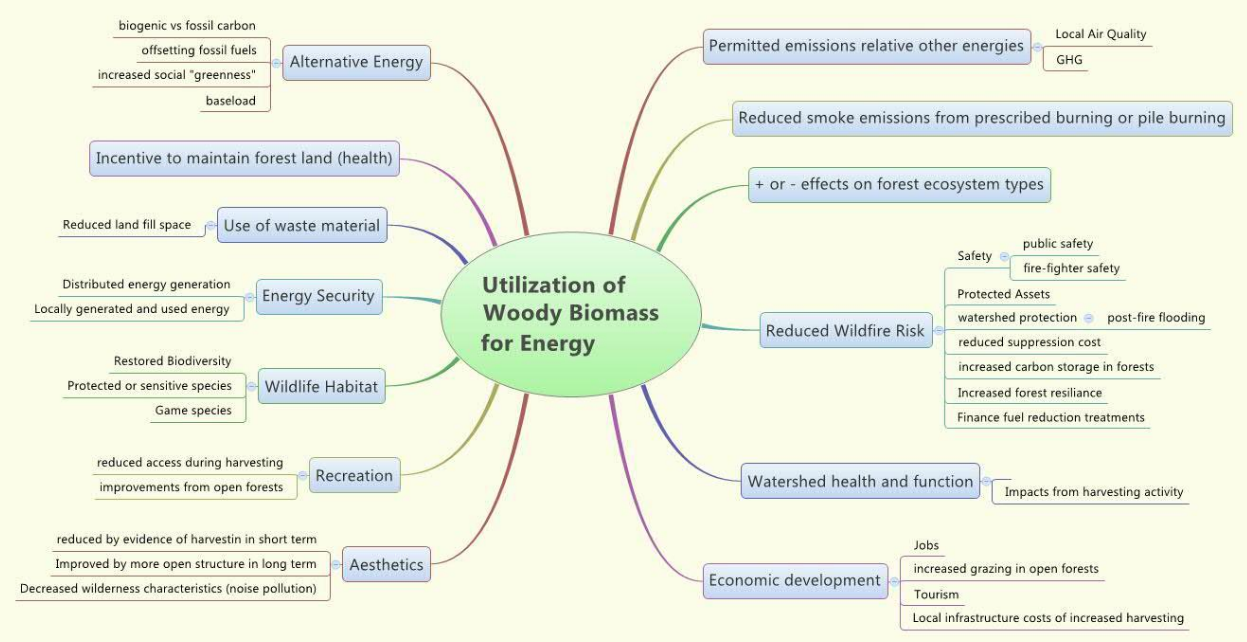
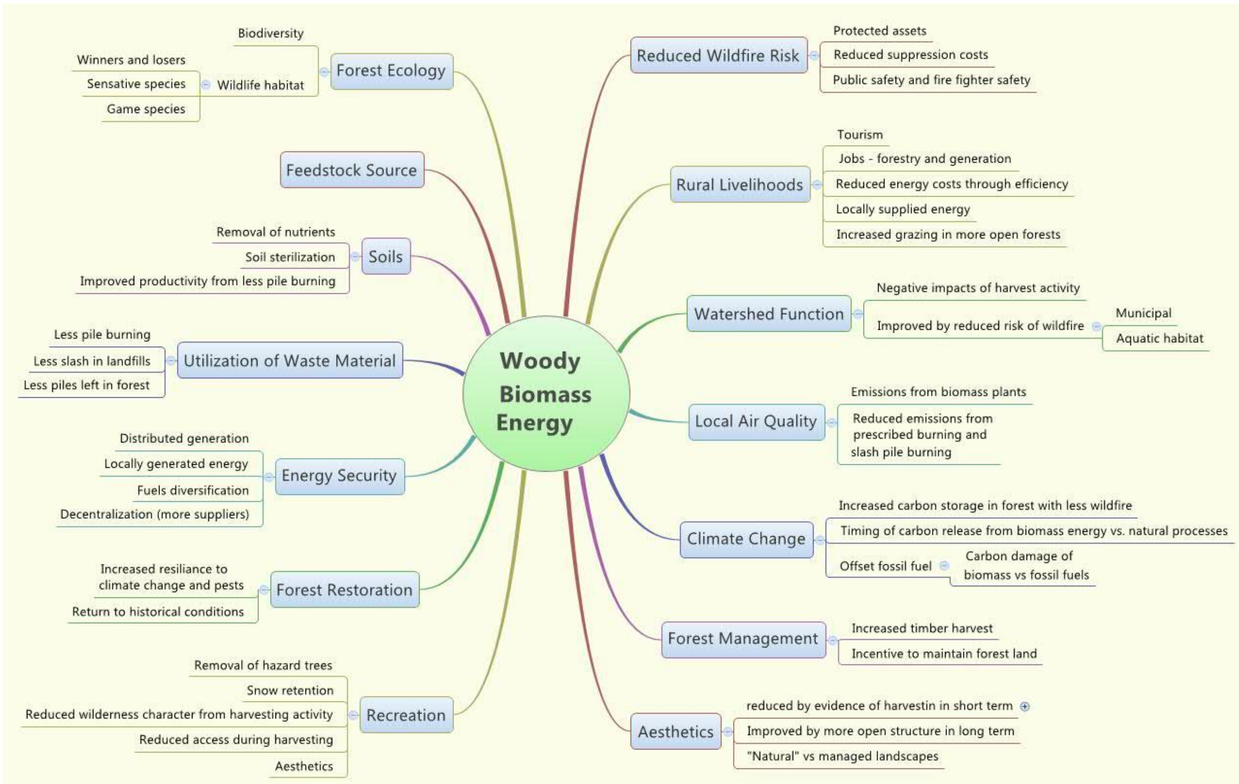


Figure A.4. Aggregate Brainstorming Map



APPENDIX B

Determination of Attribute Levels

B.1. Local Air Quality (AIRDAYS)

The number of days annually that are “Unhealthy for Sensitive Groups” was selected as the metric for the AIRDAYS attribute. “Unhealthy for Sensitive Groups” is defined by the US Environmental Protection Agency (EPA) as follows: Although general public is not likely to be affected at this AQI range, people with lung disease, older adults and children are at a greater risk from exposure to ozone, whereas persons with heart and lung disease, older adults and children are at greater risk from the presence of particles in the air. “Unhealthy” is defined by the EPA as follows: Everyone may begin to experience some adverse health effects, and members of the sensitive groups may experience more serious effects. Although a rating of “Unhealthy” air quality days is likely to resonate more strongly with respondents, emissions from potential woody biomass plants are less likely to be significant enough to cause Unhealthy air days than they are to contribute to degraded air quality of some lesser degree like Unhealthy for Sensitive Groups. Therefore, valuing impacts of increases in Unhealthy for Sensitive Groups is more informative.

Data to define the status quo for this attribute was obtained from US EPA AirData Air Quality Index (AQI) Report, for the years 2008 – 2012 (EPA 2013). The number of Unhealthy and Unhealthy for Sensitive Groups days per year were averaged across each state, for the years 2008 – 2012, based on the available monitoring sites in each state (Table. B1). There were missing observations for some sites for some years. In instances when less than 300 days of data were available for a site in a particular year, that year of data for that site was dropped.

The average number of “Unhealthy for Sensitive Groups” and “Unhealthy” days per annum for each monitoring site and each state on average are reported in table B1. Averages were highest for

Arizona and lowest for Colorado. However, the numbers in Arizona were largely driven by one monitoring site with anomalously high numbers of poor air quality days. Because of its strong influence on the number of poor air quality days per year and the small fraction of the state's population exposed to this level poor air quality days, results from the Payson, AZ monitor were not included in the computation of average annual number of Unhealthy and Unhealthy for Sensitive Groups days per year for Arizona. On average across the three states, approximately 1 day out of every 10 that is at least Unhealthy for Sensitive Groups is severe enough to be Unhealthy for the general population. This information is presented in the attribute definition.

Because the data varied substantially from community to community, it is likely that many respondents will actually experience a different number of days each year that air quality is Unhealthy for Sensitive Groups. Given this and the fact that the numbers for each state (when Payson, AZ is omitted) were fairly similar it was deemed appropriate to use one set of levels for all three states. The status quo was set at 10 days, with alternative levels of, 5, 15 and 30 days (Table. B10). The highest level was set at 30 days based on the assumption that respondents would recognize it as about a month which would help them visualize the impact of that amount air pollution on their lives.

Table B1. EPA Air Quality Index

State	Monitoring Site	Average days annually Unhealthy for Sensitive Groups (2008-2012)	Average days annually Unhealthy (2008-2012)	Average days annually at least Unhealthy for Sensitive Groups (2008-2012)
Arizona	Flagstaff	1.8	0	1.8
Arizona	Lake Havasu City-Kingman	0.2	0	0.2
Arizona	Nogales	5	0.2	5.2
Arizona	Payson	110.8	17.8	128.6
Arizona	Phoenix-Mesa-Scottsdale	70	20.2	90.2
Arizona	Prescott	0.4	0	0.4
Arizona	Show Low	0.2	0	0.2
Arizona	Sierra Vista-Douglas	1.2	0	1.2

Arizona	Tucson	3.8	0.2	4
Arizona	Yuma	9	0.4	9.4
Colorado	Boulder	5.8	0	5.8
Colorado	Canon City	N/A	N/A	0
Colorado	Colorado Springs	3.2	0	3.2
Colorado	Denver-Aurora	20	1	21
Colorado	Durango	2.4	0.2	2.6
Colorado	Fort Collins-Loveland	10.8	0	10.8
Colorado	Grand Junction	2.4	0.2	2.6
Colorado	Greeley	3.6	0	3.6
Colorado	Pueblo	0.2	0	0.2
Colorado	Silverthorne	0.0	0	0
Montana	Billings	6.2	0	6.2
Montana	Bozeman	2.4	0	2.4
Montana	Butte-Silver Bow	7	1	8
Montana	Great Falls	0.6	0	0.6
Montana	Helena	5.2	0.8	6
Montana	Kalispell	0	0	0
Montana	Missoula	27.8	6.4	34.2
State Average Values				
Arizona		25.7	5.0	30.7
Arizona (omit Payson)		12.8	3	15.8
Colorado		6.2	0.2	6.4
Montana		7.0	1.2	8.2
All States		13.1	2.1	15.2
All States (omit Payson, AZ)		**8.6**	1.4	10

Information about potential negative health effects of reduced air quality was included in the attribute definition. Short-term negative impacts of reduced air quality were based on information for the EPA's AQI website. Long-term effects were presented in terms of changes in life expectancy resulting from exposure to higher or lower numbers of Unhealthy for Sensitive Groups air days, relative to the status quo. Pope et al. (2009) estimated that long-term exposure to a 10 micrograms per cubic meter increase in fine particulate matter concentration is associated with an decrease in mean life expectancy of about 0.4 years. Thresholds for concentrations of fine particulate matter less than 2.5 micrometers in diameter (PM2.5) within the AQI classification system are presented in Table B2. The median concentration of these ranges was used to calculate the difference in average daily exposure between the status quo and alternative levels.

Table B2. EPA Air Quality Index Classification Thresholds

AQI – PM 2.5	Low threshold micrograms/cubic meter	High threshold micrograms/cubic meter
Good	0	12.0
Moderate	12.1	35.4
Unhealthy for sensitive groups	35.5	55.4
Unhealthy	55.5	150.4
Very unhealthy	150.5	250.4
Hazardous	250.5	350.4

Table B3 shows the steps involved in calculating the change in life expectancy for an average person when the number of days poor air quality days experienced annually increases from 9 Unhealthy for Sensitive Groups and 1 Unhealthy to 27 Unhealthy for Sensitive Groups and 9 Unhealthy, over the long-term. This represents the difference between the status quo number of poor air quality days and the largest level of poor air quality days. The difference in exposure between the status quo and the alternative levels was computed and the change in exposure was multiplied by the rate of change in life expectancy to estimate the change in life expectancy (in terms of number of days) associated with a long-term increase or decrease in the number of days that are at least Unhealthy for Sensitive Groups. The calculations revealed that a change from 10 days that are at least Unhealthy for Sensitive Groups annually, to 30 days that are least Unhealthy for Sensitive groups is associated with a 28 day reduction in life expectancy

Table B3. Calculation of reduced life expectancy as a result of increased PM2.5 exposure

Air quality	Exposure per day micrograms/m^3 [19]	Status Quo Days [20]	Alternative days [21]	SQ Total exposure [22]	Alternative exposure [23]	Change in Exposure [24]	Change in life expectancy [25]
Good to moderate	15	355	335	5325	5025		
Unhealthy for sensitive groups	45	9	27	405	1215		
Unhealthy	100	1	3	100	300		
Yearly Total				5830	6540	710	Minus 28 days
Daily Average				15.97	17.92	1.95	

B.2. Number of Large Wildfires (WILDFIRES)

The levels of the WILDFIRES attribute were defined in terms of the number of wildfires per year over the next ten years that burn at least 1000 acres of forest (referred to as large wildfires). The status quo level was set at 12 large wildfires per year for each of the states in the study area, with alternative levels of 6, 9 and 15 (Table. B10). The number of fires that burned at least 1000 acres in each state between 2000 and 2011 was obtained from a national fire-perimeter shapefile obtained from the Monitoring Trends in Burn Severity project (MTBS 2012).

[19] Median exposure to PM2.5 from Table B2
[20] From the last row of Table B1
[21] Highest alternative level of poor air quality days
[22] Exposure per day for each category, multiplied by the number days in each category, for the status quo
[23] Exposure per day for each category, multiplied by the number days in each category, for the alternative level
[24] Exposure under the alternative level, minus exposure under the status quo
[25] Change in exposure, multiplied by the estimated decrease in mean life expectancy for a long term 10 microgram per cubic meter increase in exposure to PM2.5 (0.4 years)

In order to obtain the data relevant to the study area some manipulation of the dataset was required. The dataset was first clipped down from the national scale to just the three study states and then narrowed to only fires that burned between 2000 and 2011. The MTBS dataset contained all types of wildfires, including ones that burned primarily in grassland, shrubland, or other non-forest vegetation types. Because the metric is defined only as *forest* fires, the dataset was limited to only those that burned primarily in conifer forests. This eliminated nearly half of the fires in the dataset. The primary vegatetion type within each fire perimeter was determined by overlaying the LANDFIRE us_105 existing vegetation type data layer on the map with the fire perimeters and using a zonal statistics tool in ArcMap to calculate which vegetation type was most prominent within each fire perimeter. The MTBS dataset also included fires that burned less than 1000 acres, so the dataset was further narrowed to include only those fires which burned at least 1000 acres, resulting in a list of all forest fires that burned at least 1000 acres between 2000 and 2011, in each state (Table B4). To obtain the average number of large forest fires in each state, the total number of large forest fires from 2000 to 2011 was divided by the number of years in the time period.

The average number of large forest fires ranged from 8 annually in Colorado, to 18 annually in Arizona, with Montana having almost 17 per year, on average. Although the numbers for Arizona and Montana are both slightly more than double the number for Colorado, an intermediate value that would serve as a realistic status quo across all three states. In part because of the high amount of variability between the number of large wildfires that burn from year to year presenting a number slightly higher or lower that the actual estimated status quo is not expected to negatively impact the believability of the scenarios in any of the three states.

Table B4. Fires per state from 2000-2011

State	Total Fires	Total Forest Fires	Total Forest Fires > 1000 acres	Average Annual Forest

				Fires > 1000 acres
Arizona	445	217	199	18.1
Colorado	202	109	84	7.6
Montana	389	221	185	16.8
Average	345.3	182.3	156.00	14.2

The average number of homes destroyed by large wildfires annually was included as background information in the definition (Table. B5). In order to obtain an estimate of how many homes were destroyed by large fires, the list obtained from the MTBS dataset was cross-referenced with data sets on fires that destroyed structures in Montana and Arizona (RMRS 2013) and a list of “major” fires in Colorado (Graham et al. 2012). The list of major fires in Colorado included the number of homes destroyed by each fire. However, the structure in the datasets for Montana and Arizona included non-home buildings like sheds. Because the information the attribute definition provided information on the number of homes, rather than number of structures, the following steps were used to estimate how many of the structures listed in the Montana and Arizona datasets were homes.

1) For each state, Google the top 5 fires and every third fire after that down to the last structure with at least 5 structures lost in order to find statistics on the number of homes destroyed.

2) Develop a multiplier based on the ratio of number of homes destroyed to total number of structures as recorded as destroyed in the RMRS (2013) datasets. Approximately 81% of the structures listed as destroyed in AZ in the RMRS dataset were estimated to be homes, while about 33% of structures listed as destroyed in MT were estimated to be homes. The multipliers were therefore 0.81 and 0.33, for AZ and MT, respectively.

3) Estimate the total number of homes destroyed by multiplying the total number of structures destroyed by large fires by the multiplier estimated in step 2.

Table B5. Structures and homes destroyed by large wildfires

State	Number of Structures destroyed	Total homes destroyed	Average homes destroyed annually
Arizona	760	617[26]	51.4
Colorado	NA	623	51.9
Montana	657	262[27]	21.8
Average		502	39.7

B.3. Number of Homes Powered With Wood (HOMES)

The amount of energy currently being generated with woody biomass in each state was estimated in order to establish a status quo level for the number of homes powered with wood attribute. To inform the selection of alternative levels and provide contextual information to respondents, potential amounts of additional available woody biomass feedstock was also estimated. The equivalent number of homes currently powered with wood ranged from 19,229 in Montana to 21,057 in Arizona, with Colorado falling in between at 19,546 (Table B6). Because all of the values were similar, the same status quo of 20,000 home equivalents was selected for all three states. Alternative levels were of 10,000, 30,000 and 50,000 were chosen (Table. B10).

Throughout the study area, woody biomass is currently used to produce thermal energy or combined thermal and electrical energy in lumber mills and large buildings like hospitals and schools. There are also a limited number of larger operations that produce electricity that is put onto the

[26] Estimated using the multiplier developed in steps 1 through 3.
[27] Estimated using the multiplier developed in steps 1 through 3.

electrical grid. In Arizona, the Novo woody biomass power plant produces electrical energy that goes onto the grid. In Colorado, the Gypsum power plant produces electrical energy that goes onto the grid. In Montana, the Stoltze lumber mill plant produces electrical energy that goes onto the grid. Although the majority of the energy currently being generated with woody biomass across the study is used on-site rather than being put into the electrical grid, it still offsets fossil fuel use by the facilities were it is utilized.

The amount of energy being generated was converted into “equivalent number of homes powered” metric because it was presumed that number of homes would be more understandable and resonate better with respondents than presenting the choice in terms of a thermal or electrical energy unit. Table B.6 lists all the known facilities within the study are that are producing energy using woody biomass and shows how much energy is produced at each facility and the steps used to arrive at number of home equivalents powered. Energy produced by primary mills is aggregated at state level. Estimates from some facilities were obtained in terms of Megawatts produced, BTU’s/hour capacity for others, and in terms of volume of woody biomass utilized for others. The average annual household consumption for each state was known in terms of Megawatthours (MWh), so woody biomass volume and BTU capacity figures were first converted in to Megawatts. To estimate the volume of woody biomass utilized annually by facilities for which only capacity in terms of BTU’s/year was known the ratio of BDT’s to capacity was averaged across the facilities for which that data was available (fuels for school facilities in Montana) and then used to estimate volume utilized based on capacity of facilities for which only BTU capacity was known (from the “Where Wood Works” publication for Colorado).

Table B6. Woody biomass energy generation facilities in Arizona, Colorado and Montana

Facility	MMBTU/hr [28]	BDT/Year[29]	MMBtu/year[30]	MWh/year [31][32]	Home equivalents powered[33]
Boulder County, CO	3	719	12374	1197	140
CSFS, CO	0	33	562	54	6
CSU Foothills, CO	2	327	5624	544	64
Gilpin Co. CO	3	719	12374	1197	140
Mountain Park Env. Center, CO	0	93	1594	154	18
Mountain Parks Electric, CO	1	240	4125	399	47
NREL Campus, CO	10	2158	37121	3590	421
Park Co. Rec. CO	1	142	2437	236	28
S. Routt Schools, CO	1	131	2250	218	26
Primary Mills, CO	N/A	37619	647047	62581	7335
Gypsum Wallboard Plant, CO	N/A	58069	998785	96600	11322
Darby Public Schools, MT	N/A	850	14620	1414	135
Victor Public Schools, MT	N/A	500	8600	832	80
Thompson Falls Public Schools, MT	N/A	400	6880	665	64
Philipsburg Public Schools, MT	N/A	580	9976	965	92
Glacier High School, Kalispell, MT	N/A	1000	17200	1664	159
U of Montana – Western, MT	N/A	3800	65360	6321	605
Townsend School District, MT	N/A	250	4300	416	40

[28] The estimates of some facilities were obtained in terms of MMBTU/hour capacity
[29] The estimates of some facilities were obtained in terms of volume of woody biomass utilized annually
[30] This is the total amount of heat energy generated. Obtained by multiplying BDT/year by "gross heating value". Gross heating value is the amount of heat energy which can be produced by a bone dry ton (BDT) of wood and is equal to 17.2 MMBTU's per BDT.
[31] BTUs were converted to electrical units by dividing BTUs by 3,412 (the number of BTU's in a kilowatthour) and then multiplied by 1000 to obtain MWhs.
[32] Less than 100% efficiency of generation was accounted for by multiplying MWhs by a conversion efficiency factor of 0.33. Conversion efficiency factor is the rate at which heat energy can be converted into electricity on the transmission grid. The rate of .33 is the factor used for coal energy production which is assumed to be similar to factor for wood energy production.
[33] The equivalent number of homes powered with wood was obtained by dividing the total Megawatts of energy generated in each state by the state average annual household consumption. Average annual energy consumption per household is 8.5 MWh in Colorado, 10.5 MWh in Montana and 12.8 MWh in Arizona (EIA 2013)

Troy Public Schools, MT	N/A	60	1032	100	10
Eureka Public Schools, MT	N/A	960	16512	1597	153
Deer Lodge Central Park Center, MT	N/A	730	12556	1214	116
DNRC Anaconda Unit Office, MT	N/A	20	344	33	3
Primary Mills, MT	N/A	99044	1703560	164764	15764
Stoltz Lumber,MT	N/A	12624	217127	21000	2009
Novo Power, AZ	N/A	150000	2580000	249531	19434
Primary Mills, AZ	N/A	12529	215502	20843	1623
Arizona Total	N/A	162529	2795502	270374	**21057**
Colorado Total	21	100250	1724293	166770	**19547**
Montana Total	N/A	120818	2078067	200985	**19230**

The potential additional feedstock that could be harvested sustainably in each state was estimated and included in the background information section (Table B7). Sustainable harvest was defined as treating 1% of "treatable acres" per year in each state. Treatable acres were defined as accessible, non-roadless and non-wilderness, public timberland that could benefit from restoration treatments.

Table B7. Potential Additional Homes Powered with Treatment Residues[34]

State	Public timberland[35]	Public timberland in need of restoration[36]	Accessible public timberland in need of restoration[37]	Total removable residues[38] (BDT)	Additional homes powered[39]
Arizona	3,451,000	2,030,000	1,218,000	7,308,000	8,205
Colorado	7,140,000	4,200,000	2,520,000	12,600,000	23,678
Montana	11,305,000	6,650,000	3,990,000	23,688,000	36,246

B.4. Forest Health and Biodiversity Conservation (FORESTS)

The status quo level for the FORESTS attribute was estimated using the Vegetation Condition Class (VCC)classification (US Department of Interior 2013). VCC categorizes departure between current vegetation conditions and reference vegetation conditions similarly to the approach outlined in the FRCC Handbook. Both FRCC and VCC reflect the degree of departure of current landscape conditions from modeled reference conditions in terms of associated vegetation. However the methodology differs in the fact that VCC is based only on departure of current vegetation conditions from reference vegetation conditions, whereas the methodology in the FRCC Guidebook also includes departure of current fire regimes from reference conditions (Hann et al. 2004).

[34] Based on values published by Rummer et al. 2005.
[35] "Timberland" is forestland capable of growing at least 20 cubic feet per acre per year and not reserved by law or administrative action from timber harvest (Rummer et al. 2005). In the Western US, about 70% of timberland is public land (Rummer et al. 2005).
[36] "Could benefit from restoration treatments" is defined as Fire Regime Condition Class (FRCC) class 2 or 3. FRCC Class 2 indicates moderate departure from historic fire regime conditions, while Class 3 indicates fire regimes that have been significantly altered (Rummer et al. 2005).
[37] "Accessible" means not reserved or high elevation and within 15 miles of major transportation infrastructure. About 60% of North American temperate forest is considered accessible (Rummer et al. 2005).
[38] 30% of removals are assumed to be residues because about 30% of current wood removal in the Western US is residues (Perlack and Stokes 2011).
[39] Calculated as in Table A7. Because some of the total removable residues is already being utilized for energy, the estimated amount of residues currently being utilized was removed from the total removable amount before calculating the additional number of homes. It was assumed that all non-lumber-mill facilities were currently utilizing residues.

VCC can be used to document possible changes to key ecosystem components, including: vegetation characteristics (species composition, structural stage, stand age, canopy closure, and mosaic pattern); fuel composition; fire frequency, severity, and pattern; and other associated disturbances, such as insect and disease mortality, grazing, and drought. Common causes of departure include advanced succession, effective fire suppression, timber harvesting, livestock grazing, introduction and establishment of exotic plant species, and introduced insects and disease.

Using the VCC raster dataset from the LANDFIRE data distribution website (US Department of Interior 2013), the percentage of forestland in each state classified in each of the three VCC levels was estimated (Table B8). The status quo for the attribute was defined in terms of the percent of forestland in each state that is classified as having a low level of departure from historic conditions (class 1). The proportion of forestland in each state classified as Condition Class 1 was similar across all three states, ranging from 20% in Colorado to 24% in Arizona, with Montana having 22%. Because all three states were similar, a common status quo of 20% was selected. Alternative levels of 10%, 20% and 60% were selected (Table. B10).

Table B8. Vegetation Condition Class of Forestland, by State

State	Class 1[40]	Class 2[41]	Class 3[42]	Class 1 acres	Class 2 acres	Class 3 acres
Arizona	24%	40%	37%	15,813,401	26,549,423	24,748,483
Colorado	20%	62%	18%	11,295,351	34,638,108	10,221,466
Montana	22%	56%	22%	17,004,019	43,635,317	17,069,528
Average	22%	52%	26%	14,704,257	34,940,949	17,346,492

B.5. Household Monthly Energy Bill (BILL)

Household monthly energy bill was selected as the payment mechanism. Household energy bill is a logical choice because a change in the mix of energy supply can impact the cost of energy. The

[40] Low level of departure from reference conditions
[41] Moderate level of departure from reference conditions
[42] Highly departed from reference conditions

average monthly energy bill in each state was calculated using the average household monthly consumption and the price per kWh (EIA 2011). Average monthly bills ranged from about $80 in Colorado and about $84 in Montana to about $118 in Arizona, with an average value across the three states of about $95 (Table B10). It was decided that these values were similar enough to present the same status quo in all three states. In order to provide a more “round” value to facilitate comparison between the status quo and alternative levels, $100 was selected as the status quo (Table. B10). Alternative levels were $80, $120, $150, $200 and $300. Although it is likely that average household energy bills will change over the next ten years due to exogenous factors, in this survey, amount of woody biomass energy produced is the only factor presented as a potential influence on household energy bills and all other factors are implicitly held constant.

Table B9. Average Household Energy Bills, by State

State	Avg. Monthly Consumption (kWh)	Price (Cents/kWh)	Avg. Monthly Bill (2011)
Arizona	1,070	11.08	$118.62
Colorado	711	11.27	$80.12
Montana	871	9.75	$84.97
Average	884	10.70	$94.57

B.6 Appendix B References

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Appendix C

Survey Instrument and Contact Materials

C.1 Contact Materials

UNIVERSITY OF MONTANA

Bureau of Business and Economic Research
Gallagher Business Building
The University of Montana
Missoula, Montana 59812-6840
Phone: 1-877-700-2237
Email: janet.stevens@business.umt.edu

<Date>

Address of recipient
....
....
....

Dear Sir or Madam,

Your household has been randomly selected as one of a small number of <Montana> households to receive a questionnaire for an important research project being conducted by the College of Forestry and Conservation at The University of Montana. You may choose to complete the survey online now at the following web address <web address>. Alternatively, if you do not complete the survey online, you will receive a hard copy in the mail that you can fill-out and mail-back.

This project concerns preferences for woody biomass energy produced from public forests in Montana, Colorado and Arizona. Woody biomass harvest and energy production can have significant impacts on forest health and biodiversity conservation, local air quality and the risk of large wildfires. Using woody biomass for energy can also reduce our need to use fossil fuels for energy, like coal, oil and natural gas.

The information you and other survey participants provide could influence state energy production portfolios and the way public forests are managed across the Mountain West.

Thank you for your time. It is only with your generous help that our research can be successful.

Sincerely,

Tyron Venn.
Associate Professor of Natural Resource Economics

COLLEGE OF FORESTRY AND CONSERVATION
Where Ideas Take Flight

Figure C1. Pre-Survey Notice – Mixed Survey Mode

Bureau of Business and Economic Research
Gallagher Business Building
The University of Montana
Missoula, Montana 59812-6840
Phone: 1-877-700-2237
Email: janet.stevens@business.umt.edu

<Date>

Address of recipient
....
....
....

Dear Sir or Madam,

Your household has been randomly selected as one of a small number of <Montana> households to receive a questionnaire for an important research project being conducted by the College of Forestry and Conservation at The University of Montana. You may choose to complete the survey online now at the following web address <web address>. Alternatively, if you do not complete the survey online, you will receive a hard copy in the mail that you can fill-out and mail-back.

This project concerns preferences for woody biomass energy produced from public forests in Montana, Colorado and Arizona. Woody biomass harvest and energy production can have significant impacts on forest health and biodiversity conservation, local air quality and the risk of large wildfires. Using woody biomass for energy can also reduce our need to use fossil fuels for energy, like coal, oil and natural gas.

The information you and other survey participants provide could influence state energy production portfolios and the way public forests are managed across the Mountain West.

Thank you for your time. It is only with your generous help that our research can be successful.

Sincerely,

Tyron Venn.
Associate Professor of Natural Resource Economics

COLLEGE OF FORESTRY AND CONSERVATION
Where Ideas Take Flight

Figure C.2. Pre-Survey Notice – Mail-Only Survey Mode

UNIVERSITY OF MONTANA

Bureau of Business and Economic Research
Gallagher Business Building
The University of Montana
Missoula, Montana 59812-6840
Phone: 1-877-700-2237
Email: janet.stevens@business.umt.edu

<Date>

Address of recipient
....
....
....

Dear Sir or Madam,

Your household has been randomly selected as one of a small number of <Montana> households to receive a questionnaire for an important research project being conducted by the College of Forestry and Conservation at The University of Montana. You may choose to complete the survey online now at the following web address <web address>. Alternatively, if you do not complete the survey online, you will receive a hard copy in the mail that you can fill-out and mail-back.

This project concerns preferences for woody biomass energy produced from public forests in Montana, Colorado and Arizona. Woody biomass harvest and energy production can have significant impacts on forest health and biodiversity conservation, local air quality and the risk of large wildfires. Using woody biomass for energy can also reduce our need to use fossil fuels for energy, like coal, oil and natural gas.

The information you and other survey participants provide could influence state energy production portfolios and the way public forests are managed across the Mountain West.

Thank you for your time. It is only with your generous help that our research can be successful.

Sincerely,

Tyron Venn.
Associate Professor of Natural Resource Economics

COLLEGE OF FORESTRY AND CONSERVATION
Where Ideas Take Flight

Figure C.3. Survey Invitation – Internet Survey Mode

UNIVERSITY OF MONTANA

Bureau of Business and Economic Research
Gallagher Business Building
The University of Montana
Missoula, Montana 59812-6840
Phone: 1-877-700-2237
Email: janet.stevens@business.umt.edu

<Date>

Dear survey recipient,

In the states of Arizona, Colorado, and Montana, more than two thirds of all public forestland could benefit ecologically from treatments to reduce tree density. Land managers and policy makers are investigating ways to facilitate more forest treatments, and one option is to generate more renewable woody biomass energy. Woody biomass harvest and energy production can have significant impacts on forest health and biodiversity conservation, local air quality and the risk of large wildfires. Using woody biomass for energy can also reduce our need to use fossil fuels for energy, like coal, oil and natural gas.

We would like any adult (18 years or older) head of your household to complete this survey. You can complete the survey online by going to the following web address now <web address>, or by filling out the hard-copy provided. We expect completing the survey should take about 30 minutes of your time. Your responses will be strictly confidential, as no personal identification information is requested, but the overall results of the survey will be made public.

The information you and other survey participants provide may influence state energy production portfolios and the way public forests are managed in your state and across the region, so please carefully consider your responses to questions in this survey. Regardless of your level of familiarity with this topic, it is important that your views are recorded so that the opinions of <Montana> residents are represented adequately in the survey.

This survey is being conducted by Dr. Tyron Venn and Mr. Robert Campbell from the College of Forestry and Conservation at The University of Montana. If you require any further information about the survey, please feel free to contact Janet Stevens at the toll-free phone number 1-877-700-2237.

We encourage you to go online or return your completed hard-copy survey in the included stamped and addressed envelope as soon as you can. If you misplace this envelope, please return the completed survey to: Bureau of Business and Economic Research, Gallagher Business Building, The University of Montana, Missoula, Montana 59812-6840.

Thank you for your participation. It is sincerely appreciated.

Tyron Venn.
Associate Professor of Natural Resource Economics

P.S. As a token of our appreciation for completing the survey, we have enclosed a $2 bill.

COLLEGE OF FORESTRY AND CONSERVATION
Where Ideas Take Flight

Figure C.4. Cover Letter – Mixed Survey Mode

UNIVERSITY OF MONTANA

Bureau of Business and Economic Research
Gallagher Business Building
The University of Montana
Missoula, Montana 59812-6840
Phone: 1-877-700-2237
Email: janet.stevens@business.umt.edu

<Date>

Dear survey recipient,

In the states of Arizona, Colorado, and Montana, more than two thirds of all public forestland could benefit ecologically from treatments to reduce tree density. Land managers and policy makers are investigating ways to facilitate more forest treatments, and one option is to generate more renewable woody biomass energy. Woody biomass harvest and energy production can have significant impacts on forest health and biodiversity conservation, local air quality and the risk of large wildfires. Using woody biomass for energy can also reduce our need to use fossil fuels for energy, like coal, oil and natural gas.

We would like any adult (18 years or older) head of your household to complete this survey. We expect completing the survey should take about 30 minutes of your time. Your responses will be strictly confidential, as no personal identification information is requested, but the overall results of the survey will be made public.

The information you and other survey participants provide may influence state energy production portfolios and the way public forests are managed in your state and across the region, so please carefully consider your responses to questions in this survey. Regardless of your level of familiarity with this topic, it is important that your views are recorded so that the opinions of <Montana> residents are represented adequately in the survey.

This survey is being conducted by Dr. Tyron Venn and Mr. Robert Campbell from the College of Forestry and Conservation at The University of Montana. If you require any further information about the survey, please feel free to contact Janet Stevens at the toll-free phone number 1-877-700-2237.

We encourage you to return your completed survey in the included stamped and addressed envelope as soon as you can. If you misplace this envelope, please return the completed survey to: Bureau of Business and Economic Research, Gallagher Business Building, The University of Montana, Missoula, Montana 59812-6840.

Thank you for your participation. It is sincerely appreciated.

Tyron Venn.
Associate Professor of Natural Resource Economics

P.S. As a token of our appreciation for completing the survey, we have enclosed a $2 bill.

COLLEGE OF FORESTRY AND CONSERVATION
Where Ideas Take Flight

Figure C.5. Cover Letter – Mail-Only Survey Mode

UNIVERSITY OF MONTANA

Bureau of Business and Economic Research
Gallagher Business Building
The University of Montana
Missoula, Montana 59812-6840
Phone: 1-877-700-2237
Email: janet.stevens@business.umt.edu

<Date>

Dear Sir or Madam,

About two weeks ago, we sent a questionnaire that asked you about your opinions on woody biomass harvest and energy production in your state. To the best of our knowledge, you have not returned the mail survey or completed the internet version of the survey.

We have already received responses from many individuals who have expressed a wide variety of different preferences for woody biomass harvest and energy production in your state. We are writing to you again because of the importance of your response to this questionnaire to help us obtain accurate results that are truly representative of the residents of your state. **The information you provide may influence state energy production portfolios and the way public forests are managed in your state and across the region.**

We would like to remind you that this survey is completely confidential and anonymous. A questionnaire identification number is printed on the back cover of the questionnaire so that we can check your name off of the mailing list when it is returned. The list of names is then destroyed so that individual names can never be connected to the results in any way. Protecting the confidentiality of people's answers is very important to us at The University of Montana.

We hope that you will complete the questionnaire soon, either online at the following address <web address>, or by filling out and returning the replacement questionnaire provided. If for any reason you prefer not to answer the survey, please let us know by returning a note or a blank questionnaire in the enclosed stamped envelope. Thank you for your participation. It is sincerely appreciated.

Tyron Venn.
Associate Professor of Natural Resource Economics

P.S. If you require any further information about the survey, please feel free to contact Janet Stevens at the toll-free phone number 1-877-700-2237.

COLLEGE OF FORESTRY AND CONSERVATION

Figure C.6. Second Cover Letter – Mixed Survey Mode

Bureau of Business and Economic Research
Gallagher Business Building
The University of Montana
Missoula, Montana 59812-6840
Phone: 1-877-700-2237
Email: janet.stevens@business.umt.edu

<Date>

Dear Sir or Madam,

About two weeks ago, we sent a questionnaire to you that asked you about your opinions on woody biomass harvest and energy production in your state. To the best of our knowledge, it has not yet been returned.

We have already received responses from many individuals who have expressed a wide variety of different preferences for woody biomass harvest and energy production in your state. We are writing to you again because of the importance of your response to this questionnaire to help us obtain accurate results that are truly representative of the residents of your state. **The information you provide may influence state energy production portfolios and the way public forests are managed in your state and across the region.**

We would like to remind you that this survey is completely confidential and anonymous. A questionnaire identification number is printed on the back cover of the questionnaire so that we can check your name off of the mailing list when it is returned. The list of names is then destroyed so that individual names can never be connected to the results in any way. Protecting the confidentiality of people's answers is very important to us at The University of Montana.

We hope that you will fill out and return the questionnaire soon, but if for any reason you prefer not to answer the survey, please let us know by returning a note or a blank questionnaire in the enclosed stamped envelope. Thank you for your participation. It is sincerely appreciated.

Tyron Venn.
Associate Professor of Natural Resource Economics

P.S. If you require any further information about the survey, please feel free to contact Janet Stevens at the toll-free phone number 1-877-700-2237.

Figure C.7. Second Cover Letter – Mail-Only Survey Mode

[insert new Um logo]

Thank you for your help!

Recently a request asking your opinions about woody biomass energy was mailed to you. If you have already completed the questionnaire, please accept our sincere thanks. If not, please do so today.

You may complete the survey on-line by entering the following, easier- to-use address in your browser address bar.

http://www.survey.umt.edu (using the search bar will not work)

Then, enter your ID [ABCD1234]

Phone: 1-877-700-2237
janet.stevens@business.umt.edu
ww.bber.umt.edu

Figure C.8. Thank You/Reminder Post-Card – Mixed Survey Mode

[insert new Um logo]

Thank you for your help!

Recently a request asking your opinions about woody biomass energy was mailed to you. If you have already completed the questionnaire, please accept our sincere thanks. If not, please do so today.

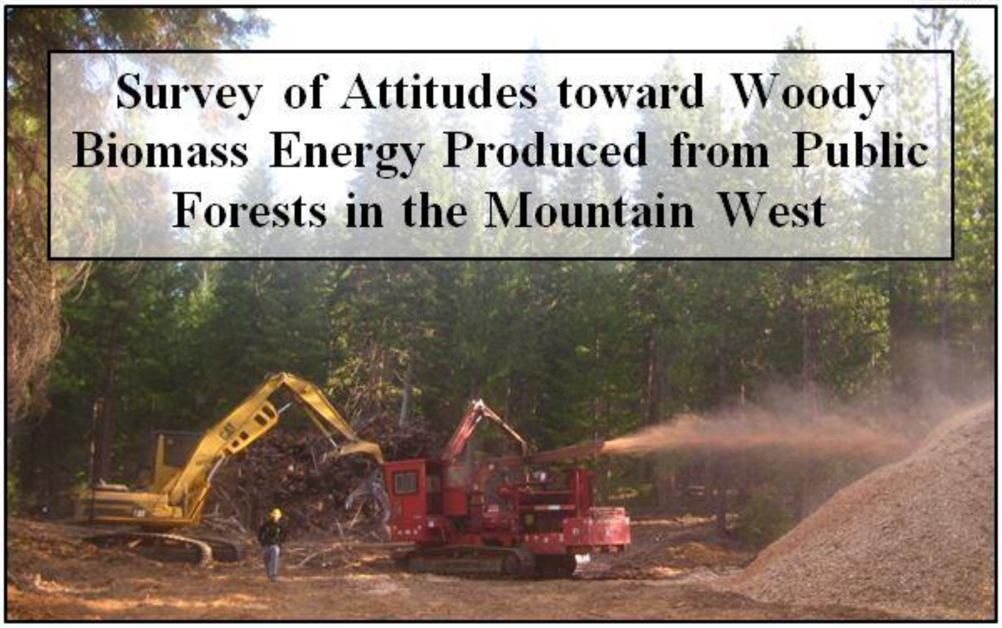
Please return the survey using the stamped envelope that you received with the questionnaire. Feel free to contact us using the information provided below if you have any questions.

Phone: 1-877-700-2237
janet.stevens@business.umt.edu
ww.bber.umt.edu

Figure C.9. Thank You/Reminder Post-Card – Mail-Only Survey Mode

C.2 Survey Instrument

Version 1



In-woods biomass chipping *Han-Sup Han, Humboldt State University*

Public land managers from county, state and federal agencies, in cooperation with researchers at the University of Montana are investigating the potential for increased amounts of energy production from woody biomass in the Mountain West. To improve future management of public forestland, these agencies would like to learn more about how you would feel about increased woody biomass energy production from public forests in your state. We would like any adult head of your household, 18 years or older, to complete this survey.

The survey has four parts. The first asks about your residence and your opinions about energy production and public land management. The second part presents you with important background information. The third part presents you with several different possible woody biomass energy production strategies for your state and asks you to select your preferred strategies. The last part of the survey asks for basic background information about you to ensure we have obtained opinions from a representative portion of residents in your state. Please complete all four parts of the survey. We will not be able to use your input if you do not **complete the survey in its entirety**.

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PART 1: YOUR RESIDENCE AND OPINIONS ABOUT ENERGY AND PUBLIC LANDS

1) **Do you live in Montana for at least half of each year?**

☐ Yes (Please answer Question 1A)

☐ No (Go to Question 2)

1A) How long have you lived in Montana?

☐ 1-4 years

☐ 5-10 years

☐ 11-19 years

☐ 20+ years

2) **What uses of your state and national forests do you value most highly? Please RANK the three (3) uses of greatest importance to you by placing a 1 on the line beside the use that is most important to you, a 2 beside your second most important use, and a 3 beside your third most important use. LEAVE ALL OTHER LINES BLANK.**

__Recreation

__Carbon sequestration

__Clean water

__Timber production

__Employment in forestry and recreation

__Pleasant views/aesthetics

__Conservation of plants and wildlife

__Clean air

__Wilderness

__Other (please list ______________________)

3) **Where would you prefer to get your household energy from? Please indicate your three (3) most preferred by placing a 1 on the line beside your most preferred, a 2 beside your second most preferred, and a 3 beside your third most preferred. LEAVE ALL OTHER LINES BLANK.**

__Coal power plants

__Natural gas power

__Oil

__Nuclear power plants

__Hydro-electric power from dams on rivers

__Woody biomass power

__Crop biomass (like corn ethanol)

__Solar energy facilities

__Wind power farms

__Geothermal power plants (using heat from the earth)

4) **Do you believe in global climate change?**

☐ Yes

☐ No

☐ I don't know

5) **Do you think that humans are causing climate change by burning fossil fuels (coal, oil and natural gas)?**

☐ Yes

☐ No

☐ I don't know

6) **What should the top priorities of U.S. national energy policy be? Please RANK the following options by placing a 1 on the line beside the priority that is most important to you, a 2 beside your second-most important priority, and a 3 beside your third most important priority.**

__Energy supply and security

__Environment and climate

__Economics and job creation

7) **Below are some issues of national concern. Please RANK the three issues of greatest importance to you by placing a 1 on the line beside the concern that is most important to you, a 2 beside your second-greatest concern, and a 3 beside your third most important concern. LEAVE ALL OTHER LINES BLANK.**

__National defense

__Climate change

__Preserving rural landscapes and lifestyles

__Social security / Social insurance

__Energy independence

__Other (please list____________________)

__Response to natural disasters

__Quality of the education system

__Quality of the healthcare system

__Economic development

__Public land management, including forest management and biodiversity conservation

Thank you for answering Part 1 of this survey.

- Starting on the next page, background information is provided that will help you evaluate potential woody biomass energy production strategies presented in Part 3 of the survey. Please take a few minutes to read this information.
- The information is followed by a few questions asking your opinion about forest management, air quality and energy policy.

PART 2: BACKGROUND INFORMATION

U.S. ENERGY CONSUMPTION AND RENEWABLE ENERGY POLICY

In 2009, about 83% of energy consumed in the US came from fossil fuels, like coal, oil and natural gas (Figure 1). In order to reduce greenhouse gas emissions and reliance on imported fossil fuels, the US government has passed legislation aimed at decreasing fossil fuels use through increased efficiency and increased production of renewable solar, wind, hydroelectric, geothermal and biomass energy[1] (information sources are indicated by raised numbers and can be found on the last page of the survey). As seen in Figure 1, about 8% of US energy presently comes from renewable sources, including about 2% from woody biomass. Studies have found that up to 10% of U.S. energy could be sustainably produced from woody biomass[2]. Consequently, woody biomass could contribute substantially more renewable energy to the nation than it does presently. In Montana, currently about 24% of energy consumed comes from renewable sources.

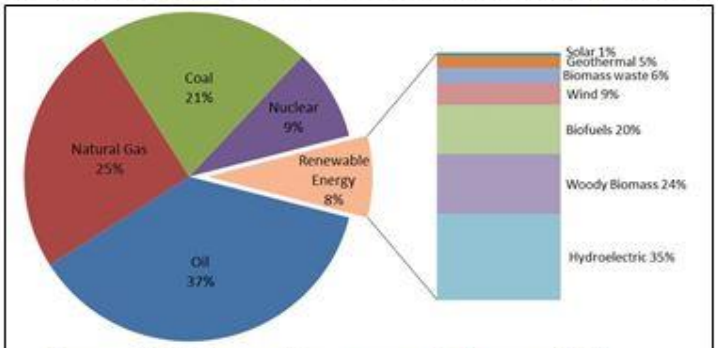

Figure 1. US Energy Consumption by Source, 2009.
Source: http://www.eia.gov/totalenergy/data/annual/archive/038409.pdf

Although renewable energy options, including woody biomass, have their own environmental impacts, they are generally considered to be preferable to fossil fuels because they are less damaging to the climate. Nuclear energy also offers a low greenhouse gas emitting option, but has high potential risks, as evidenced by the 2011 disaster in Fukushima, Japan.

WHAT IS WOODY BIOMASS AND HOW CAN IT BE USED TO PRODUCE ENERGY?

Logging and sawmilling operations generate three major sources of woody biomass that could be used for energy: 1) branches, tree-tops and needles (called residues or slash) which are too small to be used for wood products; 2) small diameter trees harvested during **forest restoration treatments** to improve forest health and reduce wildfire risk; and 3) sawdust and other wood waste materials produced at sawmills. See Photos 1 and 2.

Woody biomass can be converted into energy by burning it to produce electricity and heat energy, or by heating it in the absence of oxygen until gases are released in a process called gasification. These gases can then be burned like natural gas, or transformed into liquid biofuels like ethanol. Generating heat and electricity in these ways can be done in large-scale power plants or at smaller scales to heat and power large buildings like hospitals and schools.

Photo 1. Piled forest residues
Debbie Page-Dumroese, USFS

Photo 2. Woody biomass chips
Nate Anderson, USFS

WHAT ARE FOREST RESTORATION TREATMENTS?

- Forest health has declined in forests across Montana due to decades of successful wildfire suppression, livestock grazing, and poor timber harvesting practices in the past. This has resulted in overgrown forests that are more susceptible today to large, destructive wildfires, and insect and disease outbreaks, and which are less able to conserve the variety of native plant and animal species they did historically.
- **Forest restoration treatments** can be used to return unhealthy forests to their historic conditions through the use of light harvesting of trees, prescribed fire, or a combination of the two.

HOW MUCH WOODY BIOMASS ENERGY COULD BE SUSTAINABLY PRODUCED IN MONTANA?

- Timber harvesting activities in Montana produce forest residues and sawmill wood waste that is utilized by sawmills, schools, hospitals and other large buildings to produce both heat and electricity.
- If all this energy went toward household energy use, it would supply the annual energy demands of 20,000 homes.
- In Montana, there are approximately 4 million acres of national and state forest land in need of **forest restoration treatments** to improve forest health, which are accessible for harvesting. These forests do not include designated wilderness and roadless areas.
- If 1% of the 4 million treatable acres was treated each year to improve forest health, produce lumber and provide woody biomass for energy, enough biomass would be produced to sustainably power an additional 30,000 homes annually for a total of 50,000 homes annually.

BENEFITS AND COSTS OF WOODY BIOMASS ENERGY

The utilization of woody biomass for energy production can have the following benefits.

Benefits

- Reduce long-term impacts of climate change by displacing the use of fossil fuels.
- Improve **forest health and biodiversity conservation** in ponderosa pine and mixed conifer forest types as tree densities are reduced to be consistent with historic forest structures. Healthy forests support a greater diversity of native plant (trees, shrubs and grasses) and animal species (predators, small mammals, birds and insects), and are better able to bounce back from human and natural disturbances like insect outbreaks, non-native invasive species, disease, wildfires and a changing climate[3].
- Reduce the chance of **large wildfires** that can burn homes, endanger firefighter and civilian lives, and blanket large areas with wildfire smoke.
- Reduce the chance that **large wildfires** will damage important watersheds for municipal water supplies.
- Reduce the need for pile burning residues in the forest – a source of pollution affecting **local air quality** outside the wildfire season. Using woody biomass to produce energy is much cleaner than pile burning.
- Provide opportunities for forest managers to let ecologically beneficial, low-intensity wildfires burn to improve **forest health and biodiversity conservation**.

The utilization of woody biomass for energy can also have the following negative effects.

Costs

- If woody biomass energy does not displace locally produced fossil fuel energy, then **local air quality** will be negatively affected
- Harvesting woody biomass can decrease **forest health and biodiversity conservation** through soil compaction, loss of nutrients from forest ecosystems due to removal of biomass, increasing opportunities for spread of invasive weeds, and increasing sediment runoff into streams.

1) Do you agree with the following statements about forest management, air quality, and energy policy in your state? Please check one box for each statement.

Statement	Strongly Agree	Somewhat Agree	Neither Agree nor Disagree	Somewhat Disagree	Strongly Disagree	Don't Know
a) Public forests are in need of restoration treatments to conserve biodiversity	☐	☐	☐	☐	☐	☐
b) Public forests are in need of restoration treatments to reduce the risk of large wildfires	☐	☐	☐	☐	☐	☐
c) Public forests are in need of restoration treatments to minimize impacts from pests and disease	☐	☐	☐	☐	☐	☐
d) Creation of rural jobs should be an important consideration in the management of public forests	☐	☐	☐	☐	☐	☐
e) I support greater utilization of woody biomass from public forests for energy	☐	☐	☐	☐	☐	☐
f) I would support a large-scale woody biomass energy facility that puts electricity onto the grid in my community	☐	☐	☐	☐	☐	☐
g) I would support small-scale woody biomass energy facilities to power buildings like schools or hospitals in my community	☐	☐	☐	☐	☐	☐
h) Smoke from wildfires and burning of brush and slash piles affects the health of people in my community	☐	☐	☐	☐	☐	☐
i) Air pollution from cars, industry, power plants and fire places and wood stoves affects the health of people in my community	☐	☐	☐	☐	☐	☐
j) Utility companies should be required to produce more renewable energy	☐	☐	☐	☐	☐	☐
k) I support more renewable energy production to reduce greenhouse gas emissions	☐	☐	☐	☐	☐	☐
l) I would be willing to pay higher monthly energy bills for renewable energy	☐	☐	☐	☐	☐	☐
m) I would be willing to pay higher monthly energy bills for locally produced energy	☐	☐	☐	☐	☐	☐
n) I support expanded exploration for coal, oil and natural gas	☐	☐	☐	☐	☐	☐

Thank you for answering Part 2 of this survey.

- We would now like to know what you think about possible woody biomass energy production strategies in your state.
- On the next page are some important definitions for the remainder of the survey.
- Beginning on page 10, you will be presented with 4 **choice sets**, each of which contains the outcomes of three alternative woody biomass energy strategies.
- For each choice set, please select the **one strategy** that you most prefer.
- **Please complete ALL four choice sets.**

PART 3: WOODY BIOMASS ENERGY CHOICE SETS

- **You will need to understand the terms on these two pages to make good decisions about which woody biomass energy strategies to support.**
- Each strategy will have both positive and negative outcomes over the next ten years in terms of local air quality, forest health and biodiversity, occurrence of large, destructive wildfires, renewable energy production and cost to your household.
- The different strategies presented in the choice sets can be achieved in your state by varying how much woody biomass energy is produced, where on the landscape the woody biomass is harvested and how the woody biomass is converted into energy.
- More woody biomass energy does not necessarily result in worse air quality, fewer large wildfires, improved forest health and higher energy bills for your household.
- Other factors like climate change and population growth can also influence future outcomes.

What does "**Number of homes powered by wood**" mean?

This is a measure of the amount of woody biomass energy produced per year in your state over the next 10 years.

Heath Hildenbrand, Novo Power

Consider:

- Currently the level of woody biomass energy produced in your state is equivalent to supplying the energy demands of 20,000 homes per year.
- 50,000 homes could be sustainably powered with woody biomass from restoration treatments in national and state forests in Montana.
- This energy would be produced by a mixture of small-scale facilities, like those at schools and hospitals and large-scale power plants that put energy onto the electricity grid.
- This energy does <u>not</u> include heat produced by home wood stoves.

What does "**Number of unhealthy air days in my community**" mean?

This is the number of days per year over the next 10 years when air quality in your community is unhealthy for sensitive groups.

Chad Harder, forestpolicypub.com

Consider:

- On days when air quality is "Unhealthy for sensitive groups", older adults and children, and persons with heart, lung or respiratory diseases are at risk of respiratory problems from the presence of particles in the air. The rest of the population may experience irritation of the eyes and nose, and an increase in the incidence of respiratory illnesses, including asthma.
- Communities in your state experienced an average of 10 days annually over the last 5 years with air quality that was unhealthy for sensitive groups.
- Long-term exposure to particulate air pollution can increase occurrence of certain types of cancers and heart problems, and reduce life expectancy for all members of the population, not just sensitive individuals.
- Increasing the number of days per year that are unhealthy for sensitive groups from 10 to 30 reduces life expectancy for the average person by about 30 days[4].

What does **"Number of large wildfires in my state"** mean?

This is the number of wildfires per year over the next ten years that burn at least 1000 acres and threaten homes and important watersheds in your state.

Boise Aquatic Sciences Lab, USFS Rocky Mountain Research Station

Consider:

- An average of 12 large wildfires have occurred annually in your state over the last ten years. However, the number of large fires that burn each year is highly variable, with the potential for high numbers in active fire years and zero in other years.
- On average over the past decade, 22 homes in Montana have been destroyed each year by large wildfires. Most were destroyed by a small number of very destructive fires.
- Large wildfires have damaged thousands of acres in important watersheds, requiring millions of dollars in restoration activities and water treatment costs.
- Even if your safety and family home are not at risk, those of some of your friends and relatives may be.
- Many large wildfires, like ones that burn in wilderness, do not destroy homes or burn important watersheds and are an important beneficial natural disturbance for healthy forest ecosystems.

What does **"Forest health and biodiversity conservation"** mean?

This is the percent of healthy forestland in your state over the next ten years.

Portland Independent Media Center

Consider:

- Today approximately 20% of forestland in your state is classified as healthy[5]. As a result of fire exclusion, poor timber harvesting practices in the past and livestock grazing, The remaining 80% is not classified as healthy.
- Healthy forests support a greater diversity of native plant (trees, shrubs and grasses) and animal species (predators, small mammals, birds and insects), and are better able to bounce back from human and natural disturbances like insect outbreaks, non-native species invasion, disease, uncharacteristic wildfires and a changing climate[5].

What does **"My household's monthly energy bill"** mean?

This is your household's average monthly energy bill over the next ten years.

Businessinsider.com

Consider:

- If the current energy mix in your state does not change, the average household energy bill is expected to be about $100 per month over the next ten years.
- If a larger percentage of energy produced in your state comes from woody biomass, your energy bills are likely to be higher because of high harvest and transport costs for wood.
- However, when combined heat and electricity production are possible, and when woody biomass is available in large quantities close to power plants, woody biomass energy may be less expensive than other energy sources, resulting in lower energy bills.
- For alternatives with higher energy costs, consider what part of your household budget would be cut to pay for higher energy bills. For lower energy cost alternatives, consider where extra household income might be spent or saved.

INSTRUCTIONS FOR COMPLETING CHOICE SETS

- Choice sets will look similar to the **example** below, with three different woody biomass energy strategies presented to you.
- For each of the four choice sets on the following pages, please select the one strategy that you most prefer. You will always have the option to choose the current strategy.
- Each choice set is a separate question. Choice sets cannot be directly compared to each other.
- When deciding which strategy to select, please keep in mind your available income and all the other things you have to spend your money on, like food, clothes, housing, recreation and savings.
- **Please complete ALL four choice sets.**

EXAMPLE CHOICE SET

Attribute		Expected outcomes over 10 years		
		Strategy X	**Current Strategy**	**Strategy Y**
Homes powered with wood in your state		50,000 homes	20,000 homes	30,000 homes
Unhealthy air days in your community		5 days per year	10 days per year	30 days per year
Large wildfires in your state		15 large wildfires per year	12 large wildfires per year	6 large wildfires per year
Forest health in your state		30% healthy forests	20% healthy forests	20% healthy forests
My household's monthly energy bill		$150 ($1,800 annually)	$100 ($1,200 annually)	$80 ($960 annually)
I would choose (select one only)		☐	☐	☐

Current Strategy: This reflects the likely outcomes of the current level of woody biomass utilization in your state if that strategy continues over the next 10 years. For example, your monthly energy bill will be $100 dollars and the equivalent of 20,000 homes will be powered with woody biomass annually. You will always have the option to select the current strategy in each choice set, but this option will appear in a different column in each set.

Strategy X: This column represents a different woody biomass utilization scenario than the current strategy. As you can see, some of the outcomes are different from the current strategy column. For example, only 5 days annually have unhealthy air quality, the amount of healthy forest has increased, but the monthly cost to you would increase to $150. Strategy X will be different in each choice set.

Strategy Y: This column represents another scenario that is different from both the current strategy and Strategy X. In this strategy, the cost to you is only $80 per month, but there are 30 unhealthy air quality days every year. Strategy Y will also be different in each choice set.

Choice Set 1

Attribute		Expected outcomes over 10 years		
		Strategy A	Current Strategy	Strategy B
Homes powered with wood in my state		20,000 homes	20,000 homes	30,000 homes
Unhealthy air days in my community		5 days per year	10 days per year	10 days per year
Large wildfires in my state		15 large wildfires per year	12 large wildfires per year	6 large wildfires per year
Forest health in my state		10% healthy forests	20% healthy forests	30% healthy forests
My household's monthly energy bill		$400 ($4,800 annually)	$100 ($1,200 annually)	$120 ($1,440 annually)
I would choose (select one only)		☐	☐	☐

Please remember

- Choice sets 2 through 4 present new combinations of outcomes for woody biomass energy in Montana.
- Each choice set is a separate question. **Choice sets <u>cannot</u> be directly compared to each other.**

Choice Set 2

Attribute		Expected outcomes over 10 years		
		Current Strategy	Strategy C	Strategy D
Homes powered with wood in my state		20,000 homes	30,000 homes	50,000 homes
Unhealthy air days in my community		10 days per year	30 days per year	15 days per year
Large wildfires in my state		12 large wildfires per year	12 large wildfires per year	9 large wildfires per year
Forest health in my state		20% healthy forests	60% healthy forests	20% healthy forests
My household's monthly energy bill		$100 ($1,200 annually)	$80 ($960 annually)	$150 ($1,800 annually)
I would choose (select one only)		☐	☐	☐

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Choice Set 3

Attribute		Strategy E	Strategy F	Current Strategy
		Expected outcomes over 10 years		
Homes powered with wood in my state		30,000 homes	20,000 homes	20,000 homes
Unhealthy air days in my community		10 days per year	15 days per year	10 days per year
Large wildfires in my state		6 large wildfires per year	9 large wildfires per year	12 large wildfires per year
Forest health in my state		30% healthy forests	60% healthy forests	20% healthy forests
My household's monthly energy bill		$150 ($1,800 annually)	$80 ($960 annually)	$100 ($1,200 annually)
I would choose (select one only)		☐	☐	☐

Choice Set 4

Attribute		Strategy G	Current Strategy	Strategy H
		Expected outcomes over 10 years		
Homes powered with wood in my state		20,000 homes	20,000 homes	10,000 homes
Unhealthy air days in my community		15 days per year	10 days per year	10 days per year
Large wildfires in my state		6 large wildfires per year	12 large wildfires per year	15 large wildfires per year
Forest health in my state		60% healthy forests	20% healthy forests	10% healthy forests
My household's monthly energy bill		$200 ($2,400 annually)	$100 ($1,200 annually)	$80 ($960 annually)
I would choose (select one only)		☐	☐	☐

12

Thank you for answering Part 3 of this survey.

- We would now like to know a little about you. This will greatly assist our analysis of returned surveys, including allowing us to check if we have obtained a representative sample of the population in your state.
- All answers are **anonymous** and **confidential**.

PART 4: INFORMATION ABOUT YOU

1. **How did you feel about this survey? Beside each statement below, please check the box that most closely describes your point of view. Please give a response to every statement.**

Statement	Strongly Agree	Somewhat Agree	Neither Agree nor Disagree	Somewhat Disagree	Strongly Disagree	Don't Know
a. I would have been willing to pay more for woody biomass energy if it was produced exclusively by small-scale facilities (like those that power large buildings)	☐	☐	☐	☐	☐	☐
b. I needed more information than was provided.	☐	☐	☐	☐	☐	☐
c. The survey was confusing.	☐	☐	☐	☐	☐	☐
d. The alternative woody biomass energy strategies were unrealistic.	☐	☐	☐	☐	☐	☐
e. There are other impacts that are at least as important as homes powered with wood, my air quality, number of large, destructive wildfires, forest health and biodiversity, and cost that were not included in the choice sets. If yes, please list: ______________________ ______________________	☐	☐	☐	☐	☐	☐
f. The information presented about woody biomass energy was biased.	☐	☐	☐	☐	☐	☐
g. I already pay enough for other things and I cannot afford higher energy bills	☐	☐	☐	☐	☐	☐

2. **How much did the following factors affect your answers to the choice sets? Beside each statement below, please check the box that most closely describes your point of view. Please give a response to every statement.**

Statement	Very High		Moderate		Very Low
a. Desire to have higher amounts of woody biomass energy produced	☐	☐	☐	☐	☐
b. Concerns that more woody biomass energy could lead to more logging	☐	☐	☐	☐	☐
c. Concerns about my local air quality	☐	☐	☐	☐	☐
d. Concerns about forest health and biodiversity conservation	☐	☐	☐	☐	☐
e. Concerns about the number of large wildfires	☐	☐	☐	☐	☐
f. Concerns about increases in my household energy bill	☐	☐	☐	☐	☐

3. **What is your gender?**

☐ Male ☐ Female ☐ Other

4. **What is your age?**

☐ 18-24	☐ 45-49	☐ 70-74
☐ 25-29	☐ 50-54	☐ 75-79
☐ 30-34	☐ 55-59	☐ 80-84
☐ 35-39	☐ 60-64	☐ 85 and over
☐ 40-44	☐ 65-69	

5. **Do you speak a language other than English at home?**

☐ Yes (please answer Questions 5A and 5B)

☐ No (go on to Question 6)

5A) What is this language?

☐ Spanish ☐ Other (please list ____________)

5B) How well do you speak English?

☐ Very well ☐ Well ☐ Not well ☐ Not at all

6. At your home, do you or any member of your household have access to the internet AND own or use a desktop, laptop, netbook or notebook computer?

- ☐ Yes
- ☐ No
- ☐ I don't know

7. What is your marital status?

- ☐ Single
- ☐ Partnered
- ☐ Divorced
- ☐ Married
- ☐ Separated
- ☐ Widowed

8. Do you have children? (Check all that apply)

- ☐ No children
- ☐ Children under 18 not living with you
- ☐ Children under 18 living with you
- ☐ Children over 18 not living with you
- ☐ Children over 18 living with you

9. How do you describe yourself? (Check one or more responses)

- ☐ American Indian or Alaska Native
- ☐ Hispanic or Latino
- ☐ Asian
- ☐ Native Hawaiian or Other Pacific Islander
- ☐ Black or African American
- ☐ White

10. What is the highest level of education you have earned?

- ☐ Less than high school diploma
- ☐ Master's degree
- ☐ High school diploma or GED
- ☐ Professional degree (MD, DDS, DVM, LLB, JD, etc.)
- ☐ Associate degree
- ☐ Doctorate degree (Ph.D. or Ed.D.)
- ☐ Bachelor's degree

11. Which of the following best describes your current work status? (Check one)

- ☐ Employed full or part time
- ☐ Unemployed and not looking for work
- ☐ Active-duty military personnel
- ☐ Unemployed and looking for work
- ☐ Student
- ☐ Retired
- ☐ Homemaker
- ☐ Other (please explain) ______________________

12. Which of the following most closely represents your total household income in 2013 before taxes?

- ☐ Less than $10,000
- ☐ $50,000 to $75,000
- ☐ $10,000 to $15,000
- ☐ $75,000 to $100,000
- ☐ $15,000 to $25,000
- ☐ $100,000 to $150,000
- ☐ $25,000 to $35,000
- ☐ $150,000 to $200,000
- ☐ $35,000 to $50,000
- ☐ $200,000 or more

13. Are there any comments you would like to make?

Thank you for completing our survey.
Your time and opinions are very much appreciated!

Note: If you have misplaced the return envelope for the survey, please return it to:

Bureau of Business and Economic Research
Gallagher Business Building
The University of Montana
Missoula, Montana 59812

References

[1] 2005 US Energy Policy Act and 2007 Energy Independence and Security Act

[2] Zerbe JI (2006) Thermal energy, electricity and transportation fuels from wood, Forest Products Journal, 56(1): 6-14.

[3] United States Forest Service, Woody Biomass Utilization. http://www.fs.fed.us/woodybiomass/benefits.shtml

[4] Pope, C. Arden, Ezzati, Majid, & Dockery, Douglas W. (2009). Fine-Particulate Air Pollution and Life Expectancy in the United States. *New England Journal of Medicine, 360*(4), 376-386. doi: doi:10.1056/NEJMsa0805646

[5] Based on Vegetation Condition Class raster dataset from the USGS LANDFIRE data distribution site. http://landfire.cr.usgs.gov/viewer/

APPENDIX D

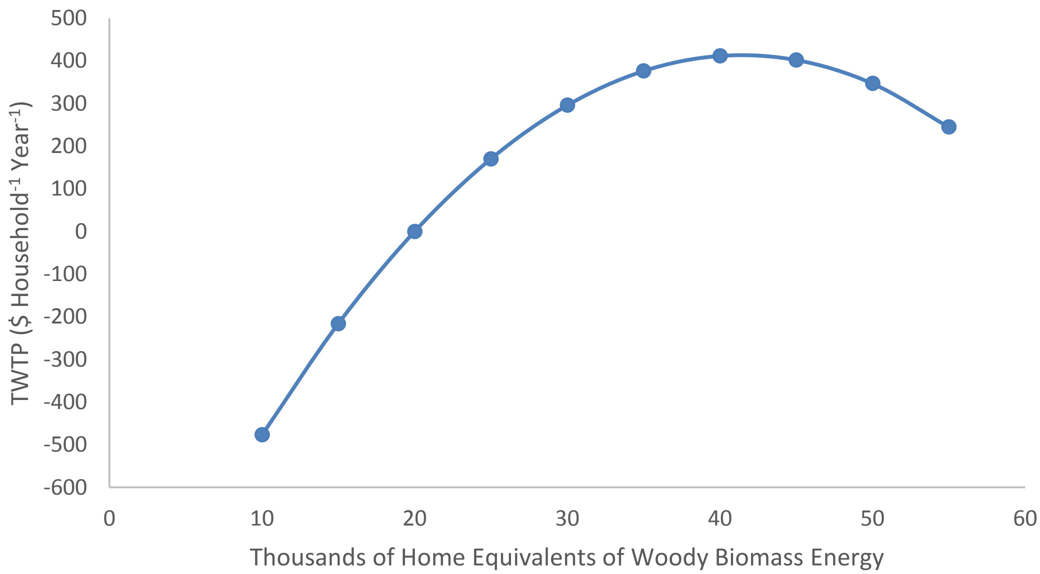
Supplementary Regression Results

Table D.1. Regression Analysis Results For Full Study Area

	Base Model		Full Model	
	Coefficient	Std. Err.	Coefficient	Std. Err.
HOMES	0.00796***	0.00169	0.0338***	0.00981
AIRDAYS	-0.0461***	0.00341	-0.0759***	0.0161
WILDFIRES	-0.0356***	0.00837	-0.0853	0.0715
FORESTS	0.0316***	0.00131	0.156***	0.00923
BILL	-0.00533***	0.000329	-0.00585***	0.000351
ASC	0.307***	0.0435	0.245***	0.0699
SKEPTIC X HOMES			-0.00685**	0.00334
SKEPTIC X AIRDAYS			0.0193***	0.00709
SKEPTIC X WILDFIRES			0.0327*	0.0174
SKEPTIC X FORESTS			-0.0132***	0.00263
HIGHINC X HOMES			0.00538	0.00390
HIGHINC X AIRDAYS			-0.0112	0.00900
HIGHINC X WILDFIRES			-0.0425**	0.0200
HIGHINC X FORESTS			0.00505	0.00326
COLLEGE X HOMES			0.00238	0.00355
COLLEGE X AIRDAYS			-0.0257***	0.00729
COLLEGE X WILDFIRES			0.00974	0.0181
COLLEGE X FORESTS			0.00606**	0.00280
SENIOR X HOMES			-0.00465	0.00360
SENIOR X AIRDAYS			0.00790	0.00710
SENIOR X WILDFIRES			-0.0317*	0.0183
SENIOR X FORESTS			-0.00230	0.00273
FORESTED X HOMES			0.00586*	0.00333
FORESTED X AIRDAYS			-0.00400	0.00700
FORESTED X WILDFIRES			-0.0339**	0.0170
FORESTED X FORESTS			0.00491*	0.00262
HOMES_SQ			-0.000440***	0.000143
AIRDAYS_SQ			0.00100***	0.000380
WILDFIRES_SQ			0.00264	0.00316
FORESTS_SQ			-0.00162***	0.000113
N	13116		12933	
log pseudolikelihood	-3879		-4136	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure C.1. Total Willingness to Pay for Woody Biomass Energy Generation, Full Study Area



Note: Figure based on Full Model from manuscript 1, using the data set for the full study area, not just Montana.

Table D2. Marginal WTP per Month – Base Model

Attribute	Arizona			Colorado			Montana		
	Average household MWTP ($)	95% confidence interval ($)		Average household MWTP ($)	95% confidence interval ($)		Average household MWTP ($)	95% confidence interval ($)	
HOMES	0.90	-0.77	2.57	1.33	0.24	2.43	1.82	1.90	2.72
AIRDAYS	-9.20	-13.78	-4.61	-10.41	-13.14	-7.69	-7.16	-9.14	-5.19
WILDFIRES	-7.19	-15.81	1.44	-6.62	-11.83	-1.41	-6.57	-10.76	-2.37
FORESTS	5.55	3.53	7.58	6.38	4.99	7.77	5.67	4.50	6.83
ASC	66.39	11.99	120.80	50.41	20.53	80.29	59.53	33.21	85.86

Table D.3. Marginal Willingness to Pay for late responders and non-late responders

Attribute	Late Responders			Non-Late Responders		
	Average household MWTP ($)	95% confidence interval ($)		Average household MWTP ($)	95% confidence interval ($)	
HOMES	0.92	-0.19	2.02	1.77	1.01	2.52
AIRDAYS	-8.36	-11.21	-5.52	-8.84	-10.74	-6.93
WILDFIRES	-7.69	-13.09	-2.30	-6.02	-9.98	-2.06
FORESTS	5.39	3.97	6.80	6.21	5.17	7.24
ASC	63.73	29.61	97.85	54.73	33.00	76.46

APPENDIX E

Stata Code for Manuscripts

MANUSCRIPT 1

```
// Robert Campbell
// Choice Experiment
// Montana Dataset
// STATA version 12.1

cd "C:\Users\robert.campbell\Desktop\finaldata"
use "Montana_Clean"

* Generate quadratic versions of attribute levels
gen homes_sq = homes^2
gen airdays_sq = airdays^2
gen wildfires_sq = wildfires^2
gen forests_sq = forests^2
gen bill_sq = bill^2

*Generate Sociodemographic and attitudinal variables
* Education
gen college =0
replace college=1 if q17==4 | q17==5 | q17==6 | q17==7

gen homescol = homes*college
gen airdayscol = airdays*college
gen wildfirescol = wildfires*college
gen forestscol = forests*college
gen billcol = bill*college
gen statusquocol = statusquo*college

* High Income
gen highinc2=0
replace highinc2=1 if q19==8 | q19==9 | q19==10
label var highinc2 "=1 if income > 100k"

gen homeshighi2 = homes*highinc2
gen airdayshighi2 = airdays*highinc2
gen wildfireshighi2 = wildfires*highinc2
gen forestshighi2 = forests*highinc2
gen billhighi2 = bill*highinc2
gen statusquohighi2 = statusquo*highinc2


*Climate Change
gen climate =0
```

```
replace climate=1 if q5==0
replace climate=1 if q5==.b
replace climate=. if q5==.
replace climate=.c if q5==.c
label var climate "=0 if believe in climate change, =1 if no or don't know"

gen manmade =0
replace manmade=1 if q6==0
replace manmade=1 if q6==.b
replace manmade=. if q6==.
replace manmade=.c if q6==.c
label var manmade "=0 if believe climate change is man made, =1 if no or don't know"

gen manmadecl =.
replace manmadecl=0 if manmade==0 & climate==0
replace manmadecl=1 if manmade==1
replace manmadecl=1 if climate==1
label var manmadecl "=zero if believe in climate change and believe it is man made"

gen homesmanmadecl = homes*manmadecl
gen airdaysmanmadecl = airdays*manmadecl
gen wildfiresmanmadecl = wildfires*manmadecl
gen forestsmanmadecl = forests*manmadecl
gen billmanmadecl = bill*manmadecl
gen statusquomanmadecl = statusquo*manmadecl


*Senior
gen senior =0
replace senior=1 if q13==10 | q13==11 | q13==12 | q13==13 | q13==14

gen homessenior = homes*senior
gen airdayssenior = airdays*senior
gen wildfiressenior = wildfires*senior
gen forestssenior = forests*senior
gen billsenior = bill*senior
gen statusquosenior = statusquo*senior


*Forested Ecoregion
gen homes_forested = homes*forested
gen airdays_forested = airdays*forested
gen wildfires_forested = wildfires*forested
gen forests_forested = forests*forested
gen bill_forested = bill*forested
gen statusquo_forested = statusquo*forested

* Low income people who selected most expensive option
gen highroller=.
replace highroller=1 if bill==400 & choice==1
gen lowincome=0
replace lowincome=1 if q19==1 | q19==2 | q19==3
gen highroller_lowincome=0
```

```
replace highroller_lowincome=1 if highroller==1 & lowincome==1
tab highroller_lowincome
*8 of the times 400 was selected it was by someone who makes less than 25k
*Drop people who are low income and selected options with highest cost
drop if highroller_lowincome==1

* Base Model
asclogit choice homes airdays wildfires forests bill statusquo ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
eststo r1

* Final Model
asclogit choice homes airdays wildfires forests bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl  ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 ///
homescol airdayscol wildfirescol forestscol  ///
homessenior airdayssenior wildfiressenior forestssenior  ///
homes_forested airdays_forested wildfires_forested forests_forested   ///
homes_sq airdays_sq wildfires_sq forests_sq  ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
eststo r2
lrtest r2 r1, force
 esttab r1 r2 using MTmodel.rtf, se title("Table 4. Regression Analysis Results") mtitles("Full Model") wide nopa
star(* 0.10 ** 0.05 *** 0.01) pr2 replace

*Bootstrap WTP
*Homes - base
bootstrap AWTP_basehomes=(-1*((_b[homes])/(_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
*Airdays - base
bootstrap AWTP_baseairdays=(-1*((_b[airdays])/(_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
*Forests - base
bootstrap AWTP_baseforests=(-1*((_b[forests])/(_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
*Wildfires - base
bootstrap AWTP_basewildfires=(-1*((_b[wildfires])/(_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
*ASC- base
bootstrap AWTP_baseASC=(-1*((_b[statusquo])/(_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

* Final Full Model
```

```
* Status quo levels are taken into account in the squared term - squared terms is multiplied by the level at which MWTP is being calculated

*Homes - full with adjustment *Using status quo levels
bootstrap AWTP_homes=(-1*((_b[homes])+(_b[homesmanmadecl]*(.52))+
(_b[homeshighi2]*(.15))+(_b[homescol]*(.29))+(_b[homessenior]*(.16))+
((_b[homes_forested])*(.56))+(20*(2*(_b[homes_sq]))))/((_b[bill]))) ///
, reps(50) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl  ///
homeshighi2 airdayshighi2 forestshighi2  wildfireshighi2 ///
homescol airdayscol wildfirescol forestscol  ///
homessenior airdayssenior wildfiressenior forestssenior  ///
homes_forested airdays_forested wildfires_forested forests_forested   ///
homes_sq airdays_sq wildfires_sq forests_sq  ///
, case(id) alt(alternative2) base("1")  noconstant

*Airdays - full with adjustment *Using status quo levels
bootstrap AWTP_airdaysadj=(-1*((_b[airdays])+(_b[airdaysmanmadecl]*(.52))+
(_b[airdayshighi2]*(.15))+(_b[airdayscol]*(.29))+(_b[airdayssenior]*(.16))+((_b[airdays_forested])*(.56))+(10*(2*(_
b[airdays_sq]))))/((_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl  ///
homeshighi2 airdayshighi2 forestshighi2  wildfireshighi2 ///
homescol airdayscol wildfirescol forestscol  ///
homessenior airdayssenior wildfiressenior forestssenior   ///
homes_forested airdays_forested wildfires_forested forests_forested   ///
homes_sq airdays_sq wildfires_sq forests_sq  ///
, case(id) alt(alternative2) base("1")  noconstant

*Forests - full with adjustment *Using status quo levels
bootstrap AWTP_forestsadj=(-1*((_b[forests])+(_b[forestsmanmadecl]*(.52))+
(_b[forestshighi2]*(.15))+(_b[forestscol]*(.29))+(_b[forestssenior]*(.16))+ ((_b[forests_forested])*(.56))
+(20*(2*(_b[forests_sq]))))/((_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl   ///
homeshighi2 airdayshighi2 forestshighi2  wildfireshighi2 ///
homescol airdayscol wildfirescol forestscol  ///
homessenior airdayssenior wildfiressenior forestssenior ///
homes_forested airdays_forested wildfires_forested forests_forested    ///
homes_sq airdays_sq wildfires_sq forests_sq  ///
, case(id) alt(alternative2) base("1")  noconstant


*Wildfires - full with adjustment + squared *Using status quo levels
bootstrap AWTP_wildfiresadj=(-1*((_b[wildfires])+(_b[wildfiresmanmadecl]*(.52))+
(_b[wildfireshighi2]*(.15))+(_b[wildfirescol]*(.29))+(_b[wildfiressenior]*(.16))+((_b[wildfires_forested])*(.56))+(12
*(2*(_b[wildfires_sq]))))/((_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl   ///
```

```
homeshighi2 airdayshighi2 forestshighi2  wildfireshighi2 ///
homescol airdayscol wildfirescol forestscol ///
homessenior airdayssenior wildfiressenior forestssenior   ///
homes_forested airdays_forested wildfires_forested forests_forested   ///
homes_sq airdays_sq forests_sq wildfires_sq ///
, case(id) alt(alternative2) base("1")  noconstant


*ASC- base - no adjustment needed because no asc interactions
bootstrap AWTP_baseASC=(-1*((_b[statusquo])/(_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl  ///
homeshighi2 airdayshighi2 forestshighi2  wildfireshighi2 ///
homescol airdayscol wildfirescol forestscol  ///
homessenior airdayssenior wildfiressenior forestssenior   ///
homes_forested airdays_forested wildfires_forested forests_forested   ///
homes_sq airdays_sq wildfires_sq forests_sq ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant


* Energy preference attitude question
gen coalpref=0
replace coalpref=1 if q4a==1 | q4a==2 | q4a==3
gen gaspref=0
replace gaspref=1 if q4b==1 | q4b==2 | q4b==3
gen oilpref=0
replace oilpref=1 if q4c==1 | q4c==2 | q4c==3
gen nucpref=0
replace nucpref=1 if q4d==1 | q4d==2 | q4d==3
gen hydropref=0
replace hydropref=1 if q4e==1 | q4e==2 | q4e==3
gen woodypref=0
replace woodypref=1 if q4f==1 | q4f==2 | q4f==3
gen croppref=0
replace croppref=1 if q4g==1 | q4g==2 | q4g==3
gen solarpref=0
replace solarpref=1 if q4h==1 | q4h==2 | q4h==3
gen windpref=0
replace windpref=1 if q4i==1 | q4i==2 | q4i==3
gen geopref=0
replace geopref=1 if q4j==1 | q4j==2 | q4j==3
tab coalpref
tab gaspref
tab oilpref
tab nucpref
tab hydropref
tab woodypref
tab croppref
tab solarpref
tab windpref
tab geopref
```

```
*Forest management, air quality and energy policy opinions
gen restoration_op = 0
replace restoration_op=1 if q9a==1 | q9a==2 | q9a==1 | q9a==2 | q9c==1 | q9c==2
label var restoration_op "=1 if agree public forests need restoration"
gen jobs_op=1
replace jobs_op=0 if q9d==1 | q9d==2
label var jobs_op "=0 if agree rural jobs should be consideration in forest management"
gen more_wbe_op =1
replace more_wbe_op=0 if q9e==1 | q9e==2
label var more_wbe_op "=0 if support more woody biomass energy from public forests"
gen lrg_wbe_op =1
replace  lrg_wbe_op=0 if q9f==1 | q9f==2
label var lrg_wbe_op "=0 if support large scale woody biomass energy facility in my community"
gen sml_wbe_op =1
replace sml_wbe_op=0 if q9g==1 | q9g==2
label var sml_wbe_op "=0 if support small scale woody biomass energy facility in my community"
gen air_smoke_op=0
replace air_smoke_op=1 if q9h==1 | q9h==2 | q9i==1 | q9i==2
label var air_smoke "=0 if smoke or air pollution negatively affects people in my community"
gen util_req_op =1
replace util_req_op=0 if q9j==1 | q9j==2
label var util_req_op "=0 if utility companies should be required to produce more reneable energy"
gen more_renew_op =1
replace more_renew_op=0 if q9k==1 | q9k==2
label var more_renew_op "=0 if support more renewable energy to reduce GHG emissions"
gen wtp_renew_op=1
replace wtp_renew_op=0 if q9l==1 | q9l==2
label var wtp_renew_op "=0 if wtp more for renewable energy"
gen wtp_local_op=1
replace wtp_local_op=0 if q9m==1 | q9m==2
label var wtp_local_op "=0 if wtop more for locally produced energy"
gen fossil_op=1
replace fossil_op=0 if q9n==1 | q9n==2
label var fossil_op "=0 if in support of more fossil fuel exploration"
gen env_priority=0
replace env_priority=1 if q7a==1
```

MANUSCRIPT 2

```
// Robert Campbell
// Choice Experiment
// Full dataset - latent class
// STATA version 12.1
* using packages lclogit and gllamm  (fmlogit must be installed for lclogit to work)
clear all
set more off
cd "C:\Users\robert.campbell\Documents\BRDI\Choice Experiment\Data\Final Data Sets"
use final_with_variables
```

```
*gen check=choice_set+entryid/10000
*choiceq is choice set number = to my choice_set
*lclogitml incorporates gllamm into lclogit
*lclogitml cannot handle "." values for choice, so they are dropped beforehand

drop if choice==.

*Final Model - 4 classes, 1 ANA constrained class
constraint 1 homes = 0
constraint 2 airdays = 0
constraint 3 wildfires = 0
constraint 4 forests = 0
constraint 5 bill = 0
constraint 6 statusquo = 0

lclogit choice homes  airdays wildfires  forests  bill statusquo, ///
group(check) id(entryid) nclasses(4) constraints(Class2 1 2 3 4 5) membership(manmadecl highinc2 college
forested confused  restoration_op air_smoke_op)  nolog seed(1234)
lclogitml
estat ic
eststo r3

esttab r3 using LCmodel2.rtf, se title("Table 4. Latent Class Regression Results") mtitles("Full Model") wide nopa
star(* 0.10 ** 0.05 *** 0.01) pr2 replace

*WTP with delta method
nlcom (-(_b[choice1: homes]/_b[choice1: bill])) (-(_b[choice3: homes]/_b[choice3: bill])) (-(_b[choice4:
homes]/_b[choice4: bill]))
nlcom (-(_b[choice1: airdays]/_b[choice1: bill])) (-(_b[choice3: airdays]/_b[choice3: bill])) (-(_b[choice4:
airdays]/_b[choice4: bill]))
nlcom (-(_b[choice1: wildfires]/_b[choice1: bill])) (-(_b[choice3: wildfires]/_b[choice3: bill])) (-(_b[choice4:
wildfires]/_b[choice4: bill]))
nlcom (-(_b[choice1: forests]/_b[choice1: bill])) (-(_b[choice3: forests]/_b[choice3: bill])) (-(_b[choice4:
forests]/_b[choice4: bill]))
nlcom (-(_b[choice1: statusquo]/_b[choice1: bill])) (-(_b[choice3: statusquo]/_b[choice3: bill])) (-(_b[choice4:
statusquo]/_b[choice4: bill]))



* MNL version of final model

asclogit choice homes airdays wildfires forests bill statusquo ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
estat ic
eststo r1


asclogit choice homes airdays wildfires forests bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl  ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol ///
homes_forested airdays_forested wildfires_forested forests_forested bill_forested   ///
homes_airsmoke airdays_airsmoke wildfires_airsmoke forests_airsmoke bill_airsmoke ///
```

```
homes_rest airdays_rest wildfires_rest forests_rest bill_rest ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
estat ic
eststo r4

 esttab r4 using LCpaperMNLmodel2.rtf, se title("Table 4. MNL Regression Results") mtitles("Full Model") wide
nopa star(* 0.10 ** 0.05 *** 0.01) pr2 replace

*WTP for MNL model
*Homes
bootstrap MNL_homes=(-
1*(((_b[homes])+(.2*(_b[homeshighi2]))+(.31*(_b[homescol]))+(_b[homes_forested])+(.48*(_b[homesmanmadecl
]))+(_b[homes_airsmoke])+(_b[homes_rest]))/(
(_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(_b[bill_forest])+(.48*(_b[billmanmadecl]))+(_b[bill_airsmoke])+(_
b[bill_rest])))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl  ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol ///
homes_forested airdays_forested wildfires_forested forests_forested bill_forested   ///
homes_airsmoke airdays_airsmoke wildfires_airsmoke forests_airsmoke bill_airsmoke ///
homes_rest airdays_rest wildfires_rest forests_rest bill_rest ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

*Airdays
bootstrap MNL_airdays=(-
1*(((_b[airdays])+(.2*(_b[airdayshighi2]))+(.31*(_b[airdayscol]))+(_b[airdays_forested])+(.48*(_b[airdaysmanmade
cl]))+(_b[airdays_airsmoke])+(_b[airdays_rest]))/(
(_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(_b[bill_forest])+(.48*(_b[billmanmadecl]))+(_b[bill_airsmoke])+(_
b[bill_rest])))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl  ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol ///
homes_forested airdays_forested wildfires_forested forests_forested bill_forested   ///
homes_airsmoke airdays_airsmoke wildfires_airsmoke forests_airsmoke bill_airsmoke ///
homes_rest airdays_rest wildfires_rest forests_rest bill_rest ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

*Forests
bootstrap MNL_forests=(-
1*(((_b[forests])+(.2*(_b[forestshighi2]))+(.31*(_b[forestscol]))+(_b[forests_forested])+(.48*(_b[forestsmanmadec
l]))+(_b[forests_airsmoke])+(_b[forests_rest]))/(
(_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(_b[bill_forest])+(.48*(_b[billmanmadecl]))+(_b[bill_airsmoke])+(_
b[bill_rest])))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl  ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol ///
homes_forested airdays_forested wildfires_forested forests_forested bill_forested   ///
```

```
homes_airsmoke airdays_airsmoke wildfires_airsmoke forests_airsmoke bill_airsmoke ///
homes_rest airdays_rest wildfires_rest forests_rest bill_rest ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

*Wildfires
bootstrap MNL_wildfires=(-
1*(((_b[wildfires])+(.2*(_b[wildfireshighi2]))+(.31*(_b[wildfirescol]))+(_b[wildfires_forested])+(.48*(_b[wildfiresma
nmadecl]))+(_b[wildfires_airsmoke])+(_b[wildfires_rest]))/(
(_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(_b[bill_forest])+(.48*(_b[billmanmadecl]))+(_b[bill_airsmoke])+(_
b[bill_rest])))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl  ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol ///
homes_forested airdays_forested wildfires_forested forests_forested bill_forested   ///
homes_airsmoke airdays_airsmoke wildfires_airsmoke forests_airsmoke bill_airsmoke ///
homes_rest airdays_rest wildfires_rest forests_rest bill_rest ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconsta

*ASC
bootstrap MNL_ASC=(-1*((_b[statusquo])/(_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl  ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol ///
homes_forested airdays_forested wildfires_forested forests_forested bill_forested   ///
homes_airsmoke airdays_airsmoke wildfires_airsmoke forests_airsmoke bill_airsmoke ///
homes_rest airdays_rest wildfires_rest forests_rest bill_rest ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

*Basic model
asclogit choice homes airdays wildfires forests bill statusquo ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

*Base Model WTP
*Homes - base
bootstrap AWTP_basehomes=(-1*((_b[homes])/(_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
*Airdays - base
bootstrap AWTP_baseairdays=(-1*((_b[airdays])/(_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
*Forests - base
bootstrap AWTP_baseforests=(-1*((_b[forests])/(_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
*Wildfires - base
```

```
bootstrap AWTP_basewildfires=(-1*((_b[wildfires])/(_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
*ASC- base
bootstrap AWTP_baseASC=(-1*((_b[statusquo])/(_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
```

MANUSCRIPT 3

```
clear all
set more off
cd "C:\Users\robert.campbell\Documents\BRDI\Choice Experiment\Data\Final Data Sets"
use final_with_variables


*IDENTIFY MODES
gen mode_internet=0
replace mode_internet=1 if hcsent==0
destring nolink, replace
gen mode_mixed=0
replace mode_mixed=1 if hcsent==1 & nolink==0
gen mode_mail=0
replace mode_mail=1 if hcsent==1 & nolink==1
replace dispx="mail" if dispx=="Mail"
gen response_internet=0
replace response_internet=1 if dispx==""
replace response_internet=1 if dispx=="email"

*DIFFERENCES BETWEEN SAMPLE CHARACTERISTICS
*ANONVA tests
oneway q13 mode, bonferroni
oneway q19 mode, bonferroni

*Chi Square Tests
tab q13 mode, cchi2 chi2 expected
tabulate q19 mode, cchi2 chi2 expected
tab male mode, cchi2 chi2 expected
tab senior mode, cchi2 chi2 expected
tab manmadecl mode, cchi2 chi2 expected

*Rate of internet access
tab q24 mode, cchi2 chi2 expected

summ college if mode_internet==1
summ college if mode_mail==1
summ college if mode_mixed==1

summ highinc2 if mode_internet==1
```

```
summ highinc2 if mode_mail==1
summ highinc2 if mode_mixed==1

summ senior if mode_internet==1
summ senior if mode_mail==1
summ senior if mode_mixed==1

summ male if mode_internet==1
summ male if mode_mail==1
summ male if mode_mixed==1


* FINAL MODEL BY MODE

*INTERNET
drop if mode_internet==0
asclogit choice homes airdays wildfires forests bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
eststo r1
esttab r1 using INTmodel.rtf, se title("Regression Analysis Results") mtitles("Full Model") wide nopa star(* 0.10 **
0.05 *** 0.01) pr2 replace

*MAIL
drop if mode_mail==0
asclogit choice homes airdays wildfires forests bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
eststo r2
esttab r2 using Mailmodel.rtf, se title("Regression Analysis Results") mtitles("Full Model") wide nopa star(* 0.10 **
0.05 *** 0.01) pr2 replace

*MIXED
drop if mode_mixed==0
asclogit choice homes airdays wildfires forests bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
eststo r3
esttab r3 using Mixedmodel.rtf, se title("Regression Analysis Results") mtitles("Full Model") wide nopa star(* 0.10
** 0.05 *** 0.01) pr2 replace

*WTP BY MODE
*INTERNET
drop if mode_internet==0
```

```
*Homes
bootstrap AWTP_INTNEWhomes=(-
1*(((_b[homes])+(.2*(_b[homeshighi2]))+(.31*(_b[homescol]))+(.14*(_b[homessenior]))+(.48*(_b[homesmanmad
ecl])))/( (_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(.14*(_b[billsenior]))+(.48*(_b[billmanmadecl]))))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

*Airdays
bootstrap AWTP_INTNEWairdays=(-
1*(((_b[airdays])+(.2*(_b[airdayshighi2]))+(.31*(_b[airdayscol]))+(.14*(_b[airdayssenior]))+(.48*(_b[airdaysmanma
decl]))) /( (_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(.14*(_b[billsenior]))+(.48*(_b[billmanmadecl]))))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

*Forests
bootstrap AWTP_INTNEWforests=(-
1*(((_b[forests])+(.2*(_b[forestshighi2]))+(.31*(_b[forestscol]))+(.14*(_b[forestssenior]))+(.48*(_b[forestsmanmad
ecl])))/( (_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(.14*(_b[billsenior]))+(.48*(_b[billmanmadecl]))))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

*Wildfires
bootstrap AWTP_INTNEWwildfires=(-
1*(((_b[wildfires])+(.2*(_b[wildfireshighi2]))+(.31*(_b[wildfirescol]))+(.14*(_b[wildfiressenior]))+(.48*(_b[wildfires
manmadecl])))/(
(_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(.14*(_b[billsenior]))+(.48*(_b[billmanmadecl]))))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconsta

*ASC
bootstrap AWTP_INTNEWASC=(-1*((_b[statusquo])/(_b[bill]))) ///
```

```
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant


*MAIL
drop if mode_mail==0

*Homes
bootstrap AWTP_MailNEWhomes=(-
1*(((_b[homes])+(.2*(_b[homeshighi2]))+(.31*(_b[homescol]))+(.14*(_b[homessenior]))+(.48*(_b[homesmanmad
ecl])))/( (_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(.14*(_b[billsenior]))+(.48*(_b[billmanmadecl]))))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

*Airdays
bootstrap AWTP_IMailNEWairdays=(-
1*(((_b[airdays])+(.2*(_b[airdayshighi2]))+(.31*(_b[airdayscol]))+(.14*(_b[airdayssenior]))+(.48*(_b[airdaysmanma
decl]))) /( (_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(.14*(_b[billsenior]))+(.48*(_b[billmanmadecl]))))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

*Forests
bootstrap AWTP_MailNEWforests=(-
1*(((_b[forests])+(.2*(_b[forestshighi2]))+(.31*(_b[forestscol]))+(.14*(_b[forestssenior]))+(.48*(_b[forestsmanmad
ecl])))/( (_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(.14*(_b[billsenior]))+(.48*(_b[billmanmadecl]))))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

*Wildfires
bootstrap AWTP_MailNEWwildfires=(-
1*(((_b[wildfires])+(.2*(_b[wildfireshighi2]))+(.31*(_b[wildfirescol]))+(.14*(_b[wildfiressenior]))+(.48*(_b[wildfires
manmadecl])))/(
(_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(.14*(_b[billsenior]))+(.48*(_b[billmanmadecl]))))) ///
```

```
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconsta

*ASC
bootstrap AWTP_MailNEWASC=(-1*((_b[statusquo])/(_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant


*MIXED
drop if mode_mixed==0

*Homes
bootstrap AWTP_MixNEWhomes=(-
1*(((_b[homes])+(.2*(_b[homeshighi2]))+(.31*(_b[homescol]))+(.14*(_b[homessenior]))+(.48*(_b[homesmanmad
ecl])))/( (_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(.14*(_b[billsenior]))+(.48*(_b[billmanmadecl]))))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

*Airdays
bootstrap AWTP_MixNEWairdays=(-
1*(((_b[airdays])+(.2*(_b[airdayshighi2]))+(.31*(_b[airdayscol]))+(.14*(_b[airdayssenior]))+(.48*(_b[airdaysmanma
decl]))) /( (_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(.14*(_b[billsenior]))+(.48*(_b[billmanmadecl]))))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

*Forests
bootstrap AWTP_MixNEWforests=(-
1*(((_b[forests])+(.2*(_b[forestshighi2]))+(.31*(_b[forestscol]))+(.14*(_b[forestssenior]))+(.48*(_b[forestsmanmad
ecl])))/( (_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(.14*(_b[billsenior]))+(.48*(_b[billmanmadecl]))))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
```

```
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant

*Wildfires
bootstrap AWTP_MixNEWwildfires=(-
1*(((_b[wildfires])+(.2*(_b[wildfireshighi2]))+(.31*(_b[wildfirescol]))+(.14*(_b[wildfiressenior]))+(.48*(_b[wildfires
manmadecl]))))/(
(_b[bill])+(.2*(_b[billhighi2]))+(.31*(_b[billcol]))+(.14*(_b[billsenior]))+(.48*(_b[billmanmadecl]))))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconsta

*ASC
bootstrap AWTP_MixNEWASC=(-1*((_b[statusquo])/(_b[bill]))) ///
, reps(500) seed(10101) cluster(entryid) idcluster(bootcl) group(id):asclogit choice homes airdays wildfires forests
bill statusquo ///
homesmanmadecl airdaysmanmadecl wildfiresmanmadecl forestsmanmadecl billmanmadecl ///
homeshighi2 airdayshighi2 wildfireshighi2 forestshighi2 billhighi2  ///
homescol airdayscol wildfirescol forestscol billcol  ///
homessenior airdayssenior wildfiressenior forestssenior billsenior   ///
, case(id) alt(alternative2) base("1") vce(cluster entryid) noconstant
```